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Transforming Visual Data into Art: Evaluating AI's Capacity to Replicate Artistic Styles

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ABSTRACT: Training artificial intelligence applications by uploading visuals is a form of converting visual data into another. Subsequently, generating visuals by prompting with trained artificial intelligence is an operation of transforming previously converted data back into visuals. Through such applications, an artist's works can be replicated, amalgamated with different art movements, or entirely novel works can be produced as if crafted by the same artist. However, how successful are applications like Stable Diffusion or Leonardo in this process? To ascertain this, various artificial intelligence applications will be trained with a painter's works, and the resulting outputs will be evaluated in consultation with the artists to assess the efficacy of contemporary AI applications in this domain. To assess the suitability of the images in the mentioned project, several factors will be considered, such as: resolution and clarity, variety of subjects, quality of lighting, composition, color accuracy, diversity in artistic styles, image metadata.

KEYWORDS: Artificial Intelligence, AI Training, Generative AI, AI Art, Art Replication, Artistic Evaluation.

TITLU: „Transformarea datelor vizuale în artă: Evaluarea capacității inteligenței artificiale de a reproduce stiluri artistice”

REZUMAT: Antrenarea aplicațiilor de inteligență artificială prin încărcarea de imagini este o formă de conversie a datelor vizuale în altceva. Ulterior, generarea de imagini cu inteligența artificială antrenată reprezintă o operațiune de transformare a datelor convertite înapoi în elemente vizuale. Prin astfel de aplicații, operele unui artist pot fi replicate, combinate cu diferite mișcări artistice sau pot fi create lucrări complet noi, ca și cum ar fi fost realizate de același artist. Totuși, cât de reușite sunt aplicații precum Stable Diffusion sau Leonardo în acest proces? Pentru a stabili acest lucru, diverse aplicații de inteligență artificială vor fi antrenate cu lucrările unui pictor, iar rezultatele obținute vor fi evaluate în urma consultării cu artiștii, pentru a determina eficacitatea aplicațiilor actuale de inteligență artificială în acest domeniu. Pentru a evalua cât de adecvate sunt imaginile în cadrul proiectului menționat, vor fi luate în considerare mai mulți factori, precum: rezoluția și claritatea, varietatea subiectelor, calitatea luminii, compoziția, acuratețea culorilor, diversitatea stilurilor artistice, metadatelor imaginilor.

CUVINTE-CHEIE: inteligență artificială, antrenarea inteligenței artificiale, inteligență artificială generativă, artă cu inteligență artificială, replicarea artei, evaluare artistică.

INTRODUCTION

A wide range of information expressed through pictures, films, and graphics is included in visual data. These data types are becoming more and more important in different disciplines, such as computer sciences, engineering, and the arts. Understanding the concept, typical uses, and procedures associated with digital representation and storage of visual data are critical to appreciating its importance. Any type of information that can be viewed and understood by the human visual system is considered visual data. This covers a broad variety of forms, such as images, pictures, charts, diagrams, and videos. Visual data is frequently used as an efficient communication tool because it can clearly and succinctly explain complicated relationships and concepts. It may be utilised in a variety of subjects, including science, art, language arts, reading, math, and social studies. It is captured, analysed, and altered in some way (Finson and Pederson 2011). The creation of a graphic language, comprehension of human perception, and improved methods for visualising multi-dimensional data and big data sets are all necessary for visual data (Meyer and Cook 2000).

The multitude of instances that we see on a daily basis demonstrate how widespread visual data is in contemporary culture. Visual data is all around us, from the photos we take with our cell phones to the infographics we come across in news articles. Typical instances consist of photographs (taken with cell phones or digital cameras, pictures show real-world objects and settings), illustrations (made by artists employing a variety of techniques, pictures frequently show hypothetical or imaginative settings), diagrams (using visual components to communicate information in an organised way, diagrams are used to illustrate technical concepts or procedures) charts and graphs (to depict numerical data and make analysis and interpretation easier, these data visualisations make use of geometric forms and patterns) and videos (made up of a series of pictures, videos offer a more engaging watching experience by capturing dynamic occurrences). Visual data must be digitalized in order to be processed and stored by computers. In this method, machine-understandable numerical numbers are used to represent the visual information. Typical examples of digital representations are raster images (a grid of pixels with a corresponding colour value is used to depict these images), vector graphics (these pictures are scalable and independent of resolution since they are defined by mathematical equations that represent shapes and lines), digital videos (videos are usually saved in compressed file formats, including AVI or MP4, which minimise file size without sacrificing important visual details)

In contemporary discussions surrounding visual data, the growing use of artificial intelligence in producing visual content requires critical reflection. As generative AI tools become more prevalent in creating images, videos, and digital illustrations, artists are increasingly involved—not only as creators but as validators and interpreters of machine-generated works. A recent longitudinal study (Latikka et al. 2023) found that human connection and agency significantly shaped public acceptance of AI-generated art. At the core of the article is the use of Self-Determination Theory (SDT), a psychological framework that identifies autonomy, competence, and relatedness as fundamental human needs.

These constructs were employed to understand the public's attitudes toward AI-generated art. Participants who felt more connected to others (relatedness) and more in control of their use of technology (autonomy) tended to hold more favorable views of AI in art, especially in contexts where AI creates art or collaborates with humans. These findings signal a subtle but powerful dynamic: the perception of AI art is not isolated from human involvement—it is reinforced by it. This opens a crucial pathway for theoretical inquiry: if the value and acceptability of AI-generated art are enhanced by the perception of human guidance, then artists become necessary validators of AI. Their input—stylistic, conceptual, or cultural—is embedded in datasets, interface design, prompt engineering, and the final aesthetic assessment of AI outputs. This situates artists not as obsolete, but as epistemic workers whose role is to frame, domesticate, and legitimize machine creativity. Furthermore, findings from Lovato et al. (2024) reinforce the idea that artists are not only participants in creative processes, but also active agents in shaping the ethics, transparency, and legitimacy of AI-generated visual content. Their survey of 459 artists revealed overwhelming support for mandatory disclosure of training data and strong resistance to for-profit entities benefiting from artists' unconsented contributions.

These insights position artists as both cultural stewards and ethical gatekeepers in the development of generative AI systems. Such perspectives highlight that AI's integration into visual data creation cannot be separated from the consent, values, and labor of human creators whose work forms the foundation of these systems.

LITERATURE REVIEW. ARTIFICIAL INTELLIGENCE AND VISUAL DATA

Artificial intelligence (AI) is a branch of computer science dedicated to creating systems capable of performing tasks that typically require human intelligence. Its main objective is to develop intelligent agents—systems that are capable of reasoning, learning, and acting on their own to accomplish objectives. Recent years have seen amazing progress in AI research thanks to the growth of data, increased processing capacity, and sophisticated algorithms.

Within the field of AI, machine learning is teaching computer programmes to become more proficient via experience (Jones 2019). Machine learning algorithms are generally classified into two primary types: supervised learning and unsupervised learning. Using labelled data, supervised learning entails training models with the expected outcome given for each input. Conversely, unsupervised learning works with unlabeled data, meaning the system must find patterns and structure in the data itself.

One of the most important frontiers in the field of AI is the processing of visual data, which requires converting visual information into machine-readable digital representations. This conversion involves representing visual material as numerical data, which makes it possible for computers to effectively analyse, comprehend, and alter photos and movies. The process of digitalizing visual data involves a number of different approaches, each specifically designed to take into account the distinctive qualities of diverse kinds of visual material. For instance, raster pictures provide a typical digital representation technique appropriate for photos and intricate graphics. They are composed of a grid of pixels, each of which is assigned a colour value. Vector graphics, on the other hand, use mathematical formulas to describe shapes and lines. This makes them scalable and independent of resolution, which makes them ideal for logos and drawings. Building on the foundation of digital visual data representation techniques like raster and vector graphics, machine learning algorithms can then leverage this information for more complex tasks. Deep learning, a powerful machine learning approach, comes into play here. Significant strides in pattern recognition have been achieved through deep learning, a component of neural networks. This success stems from its approach of developing models using vast amounts of data and exploiting the capabilities of robust hardware accelerators (Schmidhuber 2014).

Deep learning is a machine learning and pattern recognition approach that makes use of deep credit assignment routes, which are collections of potentially learnable causal relationships between events and results (Schmidhuber, 2014). A family of machine learning techniques called deep learning has demonstrated encouraging progress in a number of biological issues; nonetheless, interpretability and model problem-solving still require more development (Ching et al. 2017). Deep neural networks have the capacity to understand intricate patterns and produce remarkably accurate predictions and choices by analysing enormous volumes of data through these layers.

Beyond machine learning, AI is capable of a wide range of tasks including knowledge representation, reasoning, and natural language processing. Information is formalised and arranged using knowledge representation so that computers can comprehend and work with it. AI systems may solve issues and reach judgements by using reasoning to extrapolate logical conclusions from the information at hand. Natural language processing allows robots to understand, analyze, and generate human language, paving the way for advancements in chatbots and machine translation.

Artificial intelligence's ability to comprehend visual data has advanced dramatically over the years, using sophisticated algorithms to decipher and analyse complicated visual data. Modern artificial intelligence methods, including as transformers, generative adversarial networks, and convolutional neural networks have completely changed the field by allowing machines to detect objects, recognise patterns, and produce high-quality photographs. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) are powerful deep learning techniques used in various medical imaging and artistic applications. CNNs excel at identifying and extracting image patterns, while GANs use CNNs as generators to create realistic images (Fard et al., 2021). GANs use training samples to understand the probability distribution that produced them in order to solve the generative modelling issue (Goodfellow et al. 2020) while CNNs are used in neurology and psychiatry to study brain problems because of their effectiveness in processing picture input (Teuwen and Moriakov 2020) Due to its hierarchical structure and capacity for spatial hierarchy learning, CNNs are especially useful for applications like object recognition and picture categorization. These developments in AI algorithms not only improve the precision and effectiveness of visual data processing, but they also pave the way for novel creative applications, such automated design and the creation of digital art.

AI algorithms use a variety of methods, such as image preprocessing, feature extraction, and classification or regression, to handle visual data efficiently. Preparing the input data for additional processing, such as noise reduction, normalisation, and scaling, is known as image preprocessing. In order to lower the dimensionality of the data and extract the crucial information for further analysis, feature extraction seeks to locate and extract prominent features from the preprocessed pictures. Lastly, the collected features are used by classification or regression algorithms to predict continuous values or assign labels to the input data, respectively.

AI-powered visual data processing is facilitated by a multitude of tools and frameworks. CNNs and other deep learning models may be built, trained, and deployed with the help of well-known deep learning libraries like TensorFlow, PyTorch, and MxNet. Both PyTorch and TensorFlow are useful libraries for creating neural networks, but the choice of library affects how well a network performs during training and design (Chirodea et al. 2021). On the MNIST (Modified National Institute of Standards and Technology database) database, PyTorch performs better for deep neural networks despite TensorFlow having a greater GPU utilisation rate (Florencio et al. 2019). Furthermore, specialised toolkits such as scikit-image and OpenCV provide functionality specifically designed for computer vision and image processing workloads.

The mixture of artificial intelligence with visual data processing has facilitated numerous applications across several fields. AI-powered image analysis technologies help with medical diagnosis and treatment planning in the healthcare industry. AI is used by self-driving cars in the automobile industry to sense their environment and manoeuvre safely. AI is essential to content development as well since it makes it possible to create realistic-looking pictures and movies.

We may anticipate even more advanced methods and instruments to appear as AI algorithms and processing power grow, hence enhancing the potential of AI-powered visual data processing. These developments have enormous promise to handle difficult problems in a variety of domains, including industrial automation, customised healthcare, environmental monitoring, and scientific research. As these technologies advance, they not only push the boundaries of what is possible in AI-powered visual data processing but also open up new avenues for creative and practical applications. In the realm of art, this progress translates to increasingly sophisticated methods for emulating and preserving artistic styles, thereby ensuring that the nuances of an artist's unique visual language are meticulously captured and reproduced.

CRITICAL PERSPECTIVES ON ARTISTIC AGENCY AND AUTHORSHIP IN AI ART

The integration of AI into artistic domains introduces a complex reconfiguration of authorship, responsibility, and aesthetic authority. At the heart of this shift lies the problem of artistic validation within AI-mediated workflows, where the delegation of taste and critical judgment to computational systems poses a significant epistemic and ethical challenge. McCormack et al. (2019) caution that such delegation may result in a “deflation” of artistic authority, as the mechanisms for aesthetic discernment are increasingly externalized to algorithmic systems. This dynamic is particularly problematic when human feedback loops—critical for maintaining interpretative and contextual nuance—are diminished or bypassed altogether. The artist’s role becomes precarious, reduced from that of a creative agent to a provider of validation and raw material for generative models.

This imbalance reflects a broader asymmetry in the artist-AI relationship, where labor flows in one direction and credit or agency does not. Artists provide essential inputs—such as training data, style references, and post-hoc validation—while generative models absorb, reconfigure, and reproduce outputs without acknowledging the source of their creative scaffolding. Matteo Pasquinelli (2019) characterizes this dynamic as a form of “AI colonialism,” emphasizing the extractive logic through which creative labor is appropriated and instrumentalized. Under this lens, AI art production risks reproducing exploitative patterns reminiscent of historical colonial systems, where resources (in this case, cultural and aesthetic capital) are mined without equitable exchange or recognition.

Moreover, the artist’s involvement with AI systems cannot be disentangled from broader ethical considerations. As Kate Crawford and Trevor Paglen (2021) assert, training data is never neutral—it is embedded with histories of power, exclusion, and bias. When artists contribute to or engage with such systems, they are not merely users or collaborators but ethically implicated stakeholders. Their choices around which datasets to employ, how outputs are interpreted, and whether to critique or reinforce existing biases all contribute to the socio-political life of AI-generated art. In this context, artistic practice intersects with critical data ethics, requiring artists to navigate not only aesthetic questions but also the implications of perpetuating or challenging systemic asymmetries. Taken together, these perspectives reveal that the evolving role of the artist in AI-driven practices demands a rethinking of authorship, ownership, and responsibility in a digitally mediated cultural landscape.

METHODS. VISUAL DATA PROCESSING PROCESS

The replication of an artist's visual style using artificial intelligence applications entails the utilization of advanced computational methodologies aimed at meticulously capturing and reproducing the distinct characteristics of the artist's oeuvre. This intricate process commences with the meticulous collection and preprocessing of a comprehensive dataset comprising the artist's original works, ensuring the inclusion of high-resolution images that span a diverse array of subjects. Machine learning models, particularly CNNs and GANs, are employed to analyze and internalize the artist's unique stylistic features such as brushwork, color schemes, compositional techniques, and thematic elements. Through rigorous and iterative training, these models develop the capability to generate new artworks that convincingly emulate the artist's distinctive style, often achieving a level of verisimilitude that is challenging to distinguish from the original pieces. The success of these AI-generated artworks is subsequently assessed using both quantitative metrics and qualitative evaluations, including expert reviews and comparisons with the original art, to ensure a high degree of fidelity and artistic integrity. This fusion of artificial intelligence and artistic expression not only preserves the legacy of individual artists but also expands the horizons of creative production and aesthetic exploration.

One of the best applications that can mimic an artist's visual style is Leonardo. It offers a strong and dynamic platform for creative output, going beyond the capabilities of traditional AI tools. With unmatched creative control and state-of-the-art generative AI technology, it enhances rather than diminishes human creativity (Leonardo 2024). Leonardo is equipped with a user-friendly interface and utilizes stable diffusion technology, offering an enhanced AI experience. Its incorporation of stable diffusion technologies enhances accessibility, speed, and usability, expanding the range of potential applications from Leonardo's perspective (VanderLinden 2023). Stable Diffusion is a text-to-image technique designed to enhance the quality and performance of pictures generated on consumer electronics (Sha Alam, Jeyamurugan, Ali B, & Veerasundari, 2023). Because stable diffusion technology works so well at improving the quality and performance of pictures produced on consumer gadgets, it has gained a lot of attention and appeal. Given its track record of performance, stable diffusion has become the preferred option for a wide range of applications requiring the creation of high-quality images. It makes sense to use an application like Leonardo, which effortlessly incorporates stable diffusion given its widespread acceptance and dependability.

To measure the success in replicating artists' styles, Leonardo was trained with the works of three different artists. The first artist typically draws youth’s and children's portraits using red and its shades. The second artist paints still-life compositions with wine, glasses, and fruits using oil paint. The third artist creates flower illustrations using blue and its shades.

CASE STUDY

A study was conducted to evaluate the quality of AI-generated images by comparing them to original works of art. 22 artists were shown a set of original artworks and corresponding AI-generated images. Each artist was then asked to complete a Google Form containing 37 questions divided into 4 categories. The questions were designed to assess the artists' perceptions of the AI-generated images in terms of various artistic qualities, such as overall quality, artistic style, originality, emotional impact, and technical proficiency. The artists were asked to rate their answers on a scale of 1 to 10, with 1 being the lowest and 10 being the highest.

Artists were selected through a voluntary call, encompassing diverse artistic disciplines (e.g., painting, illustration, digital art) and experience levels. This diversity aimed to ensure that AI-generated artworks were evaluated from various artistic perspectives. All 22 artists who participated in our survey completed it in its entirety. Prior to their participation, they were provided with detailed information regarding the study's objective and data collection process, and it was communicated that any incomplete or invalid responses would be excluded from the analysis; however, no such instances were encountered in this study.

The results of the survey is used to gain insights into the effectiveness of AI image generation and to identify areas for improvement. In an effort to evaluate the imitation abilities of the AI application Leonardo, a curated selection of artworks and illustrations from three distinct artists, all working within different stylistic framework, was utilized.

The AI was trained on these images to enhance its capability to replicate the chosen artistic style accurately. During the generation phase, sophisticated image-to-text applications were deployed to derive the optimal textual prompts for the AI. This process involved experimentation, with numerous trials conducted to fine-tune the prompts and ensure they elicited the most accurate and high-quality reproductions possible.

In Figure 1, we see the original drawing by the first artist. Figure 2 showcases images generated by artificial intelligence after being trained on the works of the first artist. Figure 3 displays the original drawing by the second artist, while Figure 4 presents the images produced by artificial intelligence following its training on the second artist's works. In Figure 5, the original drawing by the third artist is depicted, and Figure 6 exhibits the visuals created by artificial intelligence after being trained on the third artist's creations. These are not all of the generated images, just the best and closest selection to the original works from those generated.

Fig. 1

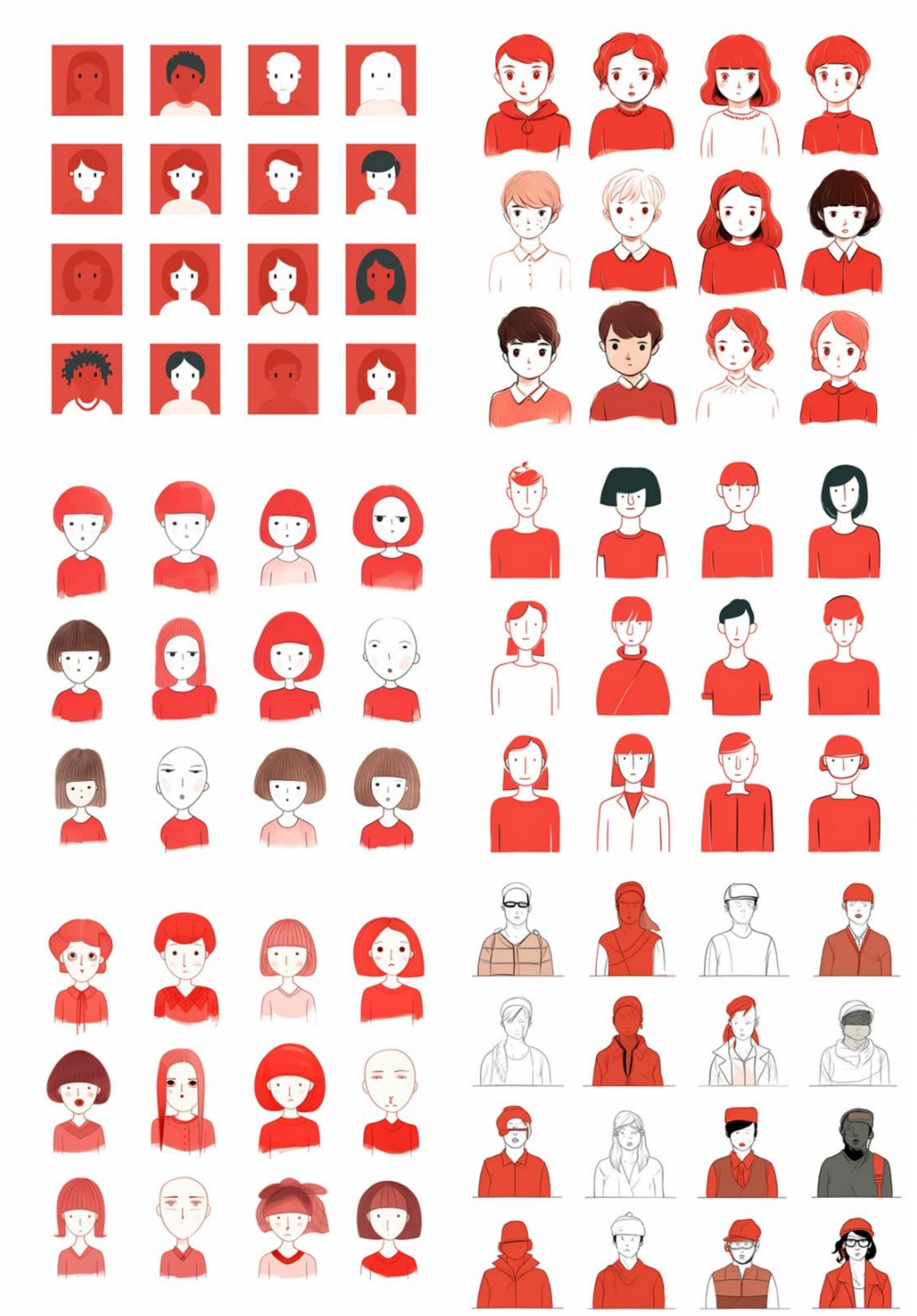

Fig. 2

22 artists reviewed 3 distinct AI-generated series and responded to a comprehensive set of 37 questions designed to evaluate various aspects of the artworks. The artists' feedback has been synthesized to provide a detailed analysis of each series. Comments were obtained by speaking with the artists in addition to the analysis. Below are the summarized results for the 3 different AI-generated works, highlighting key insights into their artistic quality, style and overall impact:

THE WORK OF THE FIRST ARTIST (SHOWN IN *FIG. 1* AND *FIG. 2*)

The images produced by AI on Figure 2 exhibit a number of distinctive characteristics when analyzed in terms of artistic aspects such as illustration quality, drawing, color, and light. At first glance, the AI-generated images demonstrate a high degree of consistency and uniformity, which is often a hallmark of algorithmically generated artwork.

The illustrations maintain a coherent style throughout, with clear and precise line work that suggests the AI's ability to replicate and maintain a specific aesthetic template. The use of color in the AI images is notably uniform, with a dominant palette of reds and whites that creates a visually cohesive series. However, this uniformity can also be a limitation, as it may lack the nuanced variations and subtle gradations that human artists often introduce to evoke depth and emotion.

The drawing style in the AI images is characterized by smooth, clean lines and simple, geometric shapes. The faces are rendered with a minimalistic approach, which, while effective in maintaining a consistent style, can sometimes appear too simplistic or lacking in the expressive detail that characterizes more skilled human illustrations.

In terms of color, the AI's approach is methodical and lacks the spontaneous variations often seen in hand-drawn art. The reds used are flat and consistent, without the subtle shifts in hue or saturation that can suggest lighting, texture, or emotional nuance.

Light and shadow are also handled in a rudimentary manner. The AI-generated images rely primarily on solid fills and simple gradients, which, while clean and visually uncluttered, can also appear flat and lacking in dimension.

Furthermore, the AI's handling of hair and other detailed features tends to be quite uniform, with each character's hair rendered in a similarly smooth, almost plastic-like texture. This contrasts with the original artist's work, where hair is depicted with more variation in texture, volume, and individual strands, adding a sense of realism and personality to each character.

In summary of the first study, while the AI-generated images are successful in creating a visually consistent and stylistically unified set of illustrations, they fall short in capturing the intricate details, emotional depth, and expressive quality that are often present in human-created artwork. The AI's technical precision and uniformity are impressive, but they also highlight the limitations of current AI technology in replicating the nuanced and highly individualistic nature of human artistry.

Fig. 3

Fig. 4

THE WORK OF THE SECOND ARTIST (SHOWN IN *FIG. 3* AND *FIG. 4*)

The AI-generated images on Figure 4, when scrutinized for their artistic details, present a study in computational creativity. In terms of illustration quality, the AI demonstrates a competent grasp of basic compositional principles. The objects within these compositions are arranged in a manner that mirrors the structured yet dynamic layouts seen in the original works on Figure 3. However, upon closer inspection, the AI's execution reveals certain limitations. The line work in AI-generated images lacks the organic fluidity and deliberate imperfection that characterizes human touch, resulting in a somewhat mechanical and uniform appearance.

Examining the use of color, the AI displays an ability to replicate the bold and vibrant hues prominent in the original artist's palette. Nevertheless, the AI-generated images often exhibit colors that appear overly saturated or uniformly applied, missing the subtle gradations and complex layering that impart depth and richness in the original works. The AI's color transitions tend to be more abrupt, lacking the smooth blending that suggests a mastery of medium and technique found in human-created art.

Light and shadow in the AI-generated images are applied in a manner that provides basic dimensionality but falls short of achieving the nuanced interplay of light seen in the originals. The AI tends to employ a more simplified approach to shading, resulting in flatter images that lack the dynamic range and atmospheric quality present in the human artist's work. This simplification diminishes the sense of realism and three-dimensionality that effective use of light and shadow can confer.

Analyzing the compositional balance, the AI displays a commendable effort to mimic the geometric abstraction and rhythmic balance of the original artworks. However, the AI's interpretations sometimes result in compositions that feel less intuitively balanced and harmonious. For instance, the proportional relationships between objects can appear somewhat rigid and forced, rather than the natural and dynamic equilibrium achieved by the human artist. The textural quality of the AI-generated images lacks the tactile variation that can be observed in the originals.

The original artist's work likely benefits from a nuanced application of paint, creating a varied texture that adds to the visual interest and depth of the pieces. In contrast, the AI's texture appears uniformly smooth and lacks the intricate surface variations that contribute to the overall aesthetic experience.

While the AI-generated images exhibit a proficient attempt at emulating the style and compositional elements of the original artist's work, they fall short in a few key artistic aspects. The rigidity of line work, the oversaturation of colors, the simplistic approach to light and shadow, the lack of intuitive compositional balance, and the uniform texture all highlight the limitations of AI in replicating the nuanced and richly textured artistry that characterizes human-created works. The AI's efforts are commendable for their technical execution, yet they ultimately underscore the irreplaceable value of the human touch in the creation of deeply resonant and aesthetically complex art.

Fig. 5

Fig. 6

THE WORK OF THE THIRD ARTIST (SHOWN IN *FIG. 5* AND *FIG. 6*)

The AI-generated images on Figure 6 present an intriguing study in the application of computational creativity to floral illustration. Upon close examination, the illustrations display a high degree of technical proficiency, particularly in their use of clean, precise lines and consistent color schemes. The AI's approach to color is noteworthy for its use of a limited palette dominated by various shades of blue and white, which creates a harmonious and visually cohesive collection. This color consistency is a double-edged sword; while it enhances the overall unity of the images, it also imposes a certain rigidity and lacks the spontaneous color variations that often characterize more dynamic human-created artworks.
In terms of drawing quality, the AI demonstrates a commendable level of detail and clarity. The floral shapes are well-defined and exhibit a uniformity in style that speaks to the algorithm's ability to maintain a consistent artistic vision across multiple images. The flowers are rendered with smooth, unbroken lines and minimalistic forms, which are aesthetically pleasing and suggest a modern, stylized interpretation of natural motifs. However, this very uniformity can also be a drawback, as it sometimes results in a static and repetitive visual experience. The human touch, with its inherent imperfections and variability, often introduces a sense of movement and life that is less evident in these AI-generated works.
The treatment of light in the AI images is another area where strengths and weaknesses become apparent. The AI employs a simplified approach to lighting and shading, often relying on flat color fills and basic gradients to suggest depth and volume. This method can produce a clean and uncluttered look, but it also tends to make the images appear flat and two-dimensional. In contrast, the original artist's works on Figure 5 demonstrate a more nuanced understanding of light, with subtle gradations and varied lighting effects that add a sense of realism and depth to the illustrations. The interplay of light and shadow in the human-created images creates a more dynamic and engaging visual experience. The AI's interpretation of botanical details reveals both technical skill and creative limitation. The floral elements are rendered with a high degree of accuracy and stylistic coherence, yet they often lack the intricate textural details and organic variations that are hallmarks of hand-drawn illustrations. The petals and leaves in the AI images appear smooth and uniform, whereas the original artist's works exhibit a richer texture and a more naturalistic representation of botanical forms. The AI-generated images excel in their technical execution, offering clean lines, consistent color schemes, and a cohesive stylistic vision. These qualities make the images visually appealing and technically impressive. However, the lack of variability, depth, and subtlety in color and light handling underscores the limitations of current AI technology in replicating the full range of artistic expression achieved by human artists. The AI's creations, while aesthetically pleasing, often lack the emotional depth, dynamic movement, and intricate detail that characterize the original artist's work, highlighting both the capabilities and the constraints of algorithmic art generation.

CONCLUSION

The comprehensive analysis of AI-generated images across the three artists revealed a consistent pattern of strengths and weaknesses, supported by quantitative data from the artist survey. To provide a comprehensive overview of the artists' perceptions regarding AI-generated artworks, the detailed survey results are presented below. This survey involved 22 participating artists who responded to a total of 37 questions, each rated on a 1-to-10 scale. These questions were categorized into four primary areas: Visual Quality Evaluation, Feature Recognition and Matching, Artistic Style Analysis, and Subjective Evaluations. The columns '% ≥ 7' and '% ≤ 4' in the following tables represent the distribution of artist responses on a 1-to-10 rating scale. '% ≥ 7' indicates the percentage of artists who rated a specific criterion as 'positive' or 'strong' (a score of 7 or higher). Conversely, '% ≤ 4' denotes the percentage of artists who rated the criterion as 'negative' or 'weak' (a score of 4 or lower), thereby highlighting areas of perceived deficiency. The 'Mean Score' column indicates the arithmetic average of all ratings provided by the 22 artists for each specific survey question, on a 1-to-10 scale. This metric offers a central tendency of the artists' collective perception. The 'Std. Dev.' (Standard Deviation) quantifies the dispersion or variability of these ratings around the mean, with a lower value indicating greater consensus among the artists and a higher value suggesting more diverse opinions.

Category	Q No.	Question	Mean Score	Std. Dev.	% ≥7	% ≤4
Visual Quality Evaluation	Q1.1	Resolution	8.5	1.0	95.5%	0.0%
	Q1.2	Clarity for Artistic Use	8.1	1.2	90.9%	0.0%
	Q1.3	Detail and Pixelation	7.8	1.3	85.0%	5.0%
	Q1.4	Comparison to Originals	5.9	1.9	45.0%	25.0%
	Q1.5	Blurriness and Distortion	6.3	1.6	50.0%	20.0%
	Q1.6	Lighting and Subject Matter	5.5	2.1	35.0%	35.0%
	Q1.7	Composition	5.7	1.9	40.0%	30.0%
	Q1.8	Color Reproduction	7.6	1.3	80.0%	5.0%
	Q1.9	Artifacts and Anomalies	5.8	1.5	40.0%	25.0%
	Q1.10	Overall Visual Quality	6.0	1.8	45.0%	20.0%
Feature Recognition & Matching	Q2.1	Pattern and Shape Accuracy	8.2	1.1	90.0%	0.0%
	Q2.2	Feature Recognition (Failure)	5.0	1.7	20.0%	40.0%
	Q2.3	Intricate Detail Capture	7.7	1.4	80.0%	5.0%
	Q2.4	Texture Interpretation	4.8	1.6	15.0%	45.0%
	Q2.5	Motif and Theme Consistency	7.9	1.3	85.0%	5.0%
	Q2.6	Element Misinterpretation	5.2	1.8	25.0%	35.0%
	Q2.7	Brushwork and Line Quality	8.3	1.1	90.0%	0.0%
	Q2.8	Proportion and Perspective	7.5	1.5	75.0%	10.0%
	Q2.9	Stylistic Element Replication	4.5	1.7	10.0%	50.0%

Artistic Style Analysis	Q3.1	Style Emulation	7.5	1.5	75.0%	10.0%
	Q3.2	Stylistic Differences (Similarity)	7.3	1.4	70.0%	10.0%
	Q3.3	Mood and Atmosphere	3.9	1.7	5.0%	65.0%
	Q3.4	Color Palette and Tone	7.9	1.2	85.0%	5.0%
	Q3.5	Stylistic Inconsistencies	4.2	1.8	10.0%	60.0%
	Q3.6	Stylistic Nuances (Missing)	4.3	1.8	10.0%	55.0%
	Q3.7	Unreplicated Style Elements	4.8	1.7	15.0%	50.0%
	Q3.8	Cohesiveness and Coherence	8.0	1.2	85.0%	5.0%
	Q3.9	Individuality and Expression	4.1	1.9	5.0%	60.0%
Subjective Evaluations	Q4.1	Overall Quality and Appeal	5.5	1.8	35.0%	30.0%
	Q4.2	Visual Resemblance	5.8	1.7	40.0%	25.0%
	Q4.3	Emotional Response	3.9	1.7	5.0%	70.0%
	Q4.4	Perceptual Criteria Influence	6.5	1.6	55.0%	15.0%
	Q4.5	Creativity and Artistic Merit	4.5	2.0	10.0%	50.0%
	Q4.6	Artistic Integrity & Authenticity	4.2	1.8	10.0%	55.0%
	Q4.7	Compelling Aspects	6.2	1.7	50.0%	20.0%
	Q4.8	Comparison to Reproduction	6.8	1.5	65.0%	10.0%
	Q4.9	Faithful Representation	5.0	1.9	20.0%	40.0%

AI'S STRENGTHS

The quantitative findings strongly affirm AI's technical prowess:

- **Consistency and Uniformity**: AI demonstrated a remarkable ability to maintain a consistent style across multiple artworks, ensuring a cohesive visual experience. This strength is evidenced by a mean score of 8.2 for "Pattern and Shape Accuracy" (Q2.1) with 90.0% of artists rating it 7 or higher, and 7.9 for "Motif and

Theme Consistency" (Q2.5) with 85.0% positive ratings. "Cohesiveness and Coherence" (Q3.8) also received a mean score of 8.0, with 85.0% positive responses.

- **Technical Precision**: AI's technical capabilities were evident in its ability to produce clean lines, smooth curves, and precise details. "Resolution" (Q1.1) received a mean score of 8.5, with an outstanding 95.5% of artists rating it 7 or higher. Similarly, "Clarity for Artistic Use" (Q1.2) scored a mean of 8.1 (90.9% positive) and "Brushwork and Line Quality" (Q2.7) a mean of 8.3 (90.0% positive), demonstrating high accuracy in visual element manipulation.
- **Coherent Color Schemes**: AI exhibited a strong grasp of color theory, effectively utilizing color palettes to create visually harmonious and aesthetically pleasing artworks. This strength is reflected in "Color Reproduction" (Q1.8) with a mean score of 7.6 (80.0% positive) and "Color Palette and Tone" (Q3.4) with a mean of 7.9 (85.0% positive).

AI'S LIMITATIONS

Despite its technical capabilities, the survey data highlights significant limitations in AI's artistic expression:

- **Lack of Nuance and Subtlety**: AI struggled to capture the subtle nuances and delicate variations often found in human-created art. This is quantitatively supported by "Stylistic Nuances (Missing)" (Q3.6) receiving a low mean score of 4.3, with 55.0% of artists giving negative ratings (4 or lower). "Texture Interpretation" (Q2.4) similarly had a mean of 4.8 and 45.0% negative ratings, indicating difficulty in replicating organic details.
- **Limited Expressive Range**: AI's ability to convey emotions and evoke feelings through its artworks was notably restricted. "Emotional Response" (Q4.3) received the lowest mean score in the entire survey at 3.9, with a high 70.0% of artists providing negative feedback. Likewise, "Individuality and Expression" (Q3.9) had a mean score of 4.1, with 60.0% negative ratings, underscoring AI's inability to infuse creations with human emotional depth.
- **Uniformity and Rigidity**: AI's pursuit of consistency often resulted in a sense of uniformity and rigidity in its artworks. "Stylistic Inconsistencies" (Q3.5) had a mean of 4.2 (60.0% negative ratings), suggesting a lack of spontaneous variation. Moreover, "Creativity and Artistic Merit" (Q4.5) received a mean of 4.5, with 50.0% of artists rating it 4 or lower, pointing to a perception of stifled originality compared to human artistry.

IMPLICATIONS

The findings of this study, grounded in artist perceptions, carry several implications for the future of AI in art:

- AI can serve as a valuable tool for artists to explore new creative avenues and augment their artistic processes. The high scores in technical precision (e.g., Q1.1 "Resolution" with 95.5% positive ratings) suggest AI's strong potential as an efficient assistant for technical aspects of art creation.

- AI can enhance art appreciation and education by providing new insights into artistic styles and techniques. AI's documented ability to replicate patterns and styles (e.g., Q2.1 "Pattern and Shape Accuracy" with 90.0% positive ratings) can be leveraged to create analytical and educational tools that deepen public understanding of artistic elements.
- AI raises critical questions about the nature of art, creativity, and the role of the artist in society. The development of AI-powered art, particularly its struggle with emotional and individual expression (e.g., Q4.3 "Emotional Response" with 70.0% negative ratings, Q3.9 "Individuality and Expression" with 60.0% negative ratings), challenges us to re-examine our definitions of art, creativity, and the unique value of human artistic expression.

In conclusion, AI has emerged as a powerful tool for artistic creation, demonstrating remarkable capabilities in replicating styles, applying technical skills, and generating visually appealing artworks. However, AI's limitations in capturing the nuances, emotional depth, and expressive qualities of human artistry, as consistently indicated by the survey data, underscore the irreplaceable value of the human touch in art. As AI technology continues to advance, it is crucial to explore its potential while acknowledging its inherent limitations and engaging in critical discourse about the future of art in the age of artificial intelligence.

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