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Using Image Similarity Metrics to Discriminate Between DALL-E Generated Art and Original Art

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ABSTRACT

The rise of image-generating artificial intelligence (AI) tools like OpenAI's DALL-E has changed the way art is made. It brings up important questions about originality, authorship, and ethical implications. I explore the originality of AI generated art through a quantitative similarity analysis using Bhattacharyya distance and Euclidean distance to measure color and structural similarity between AI outputs and their reference artworks. I analyze three distinct prompt variations—one including the artist's name, another with a detailed description but no artist reference, and a third requesting a reinterpretation rather than replication of an original painting, namely the Mona Lisa. I find that AI generated images exhibit varying degrees of similarity depending on prompt specificity. The metrics found that mentioning the artist's name in the prompt resulted in more similar outputs than when asked for a direct reinterpretation. Similarity metrics indicate that AI generated outputs tend to resemble each other more closely than they do the original painting, implying that AI models operate based on learned visual patterns rather than direct replication. The study emphasizes how important it is to have explicit ethical guidelines and legal frameworks to be able to regulate AI's influence in the artistic domain.

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1. INTRODUCTION

The rise of AI tools has revolutionized the creative field, particularly in the industry of art and literature. AI driven tools, such as language models and image generators, have opened up new avenues for creative expression and artistic exploration. However, AI being employed in art domains is raising questions on the boundaries of human creativity, authorship, and the ethics of art. Scholars argue that "AI-generated content challenges not only originality but also the very framework of copyright and intellectual property law" [1]. In this paper, we investigate the ethical issues involved in art created by AI, focusing on the tension between originality and plagiarism with respect to varying prompt information [1], [2].

AI models, such as DALL-E and Stable Diffusion, have demonstrated amazing capabilities in generating realistic and creative images from textual prompts. However, using training datasets scraped from the internet raises concerns over copyright infringement and plagiarism of existing artworks. According to [3], AI art "raises fundamental questions about the nature of creativity and whether machines can genuinely innovate or simply remix." Whether AI generated images could be considered original creations or even instances of plagiarism depend on the level of resemblance between these outputs and the training data [4], [5].

Ethical frameworks, such as Constitutional AI, are instrumental in directing the behavior of AI–aligning its outputs with ethical principles. By establishing guidelines for ethical decision-making within AI models, CAI seeks to reduce biases, enhance transparency, and ensure that art generated by AI honors human diversity and creativity [6], [7]. The evolution of models for AI generated art, including Deep Floyd IF and Midjourney, underscores the intricate nature of ethical considerations in the creative process [8].

As AI generated art increasingly blurs the lines between human and machine creativity, the necessity for perspicuous ethical guidelines and legal frameworks becomes more apparent. Through the analysis of AI generated images exploiting similarity metrics such as Bhattacharyya distance and Euclidean distance, this study aims to offer empirical insights into the originality of AI art and its concerns regarding plagiarism [9], [10]. This study contributes to the already heated debate on the confluence of AI and creativity with a comprehensive analysis of the ethical and legal issues surrounding AI art [11], [12].

As AI generated art continues to blur the line between human and machine creativity, clear ethical guidelines and legal frameworks are becoming increasingly necessary. Research by [6] suggests that "crafting effective prompts is becoming a form of artistic authorship in its own right." To contribute empirical insights to this discussion, this study analyzes AI generated images using similarity metrics such as Bhattacharyya distance and Euclidean distance–two mathematical techniques used to measure the resemblance between AI generated outputs and existing images [3], [8], [13]. Bhattacharyya distance quantifies the similarity between probability distributions, helping assess how closely an AI generated image aligns with known patterns in its training data. Euclidean distance, on the other hand, measures the straight-line difference between key features of images, offering another way to determine originality [14]–[16]. By applying these methods, this study seeks to provide objective data on how prompt specificity impacts the uniqueness of AI generated artwork [17], [18].

The gap that exists in the empirical research quantifying the relationship between the detail of the prompt and originality in the output of an AI's artwork needs to be addressed. This paper tries to bridge this gap by the empirical measurement of similarities in the AI output with regard to the training data based on metrics such as Bhattacharyya distance and Euclidean distance [19], [20]. Thus, providing empirical evidence toward the ongoing discourse on originality and plagiarism in AI generated art.

2. LITERATURE REVIEW

The introduction of AI in the arts has revolutionized traditional ways of creating, with AI offering novel tools that help expand the boundaries of human creativity while also raising serious concerns about ethics. AI generated art has brought discussions of originality, authorship, and plagiarism to the fore, challenging traditional notions of creativity and ownership. This literature review aims to take an in-depth look at the significant studies, framework, and ethical considerations relating to AI generated art and the ethical implications associated with originality and plagiarism in this new field.

2.1 Ethical Frameworks in Artificial Intelligence Art

One of the major points of discussion in AI generated art has been the ethical framework leading the development and use of AI models. Constitutional AI, or CAI, has been one approach to training language models with ethical guidelines built into their decision-making [8]. By embedding a "constitution" within AI models, CAI seeks to reduce bias, increase scalability, and better align with ethical results, making sure the outputs by AI are aligned with the principles of safety, fairness, and transparency. Think of Constitutional AI (CAI) like giving AI a moral range, it's trained to follow a set of principles, kind of like a built-in guide for making fair and ethical choices. Instead of just spitting out answers based on raw data, the AI learns to prioritize things like fairness, honesty, and reducing harm. Researchers teach it by giving feedback, almost like coaching, so it knows which responses align with these values and which don't. This helps prevent biased or harmful answers, makes the AI more independent (so people don't have to constantly monitor it), and keeps it reliable across different situations. This framework holds particular relevance in the context of AI art, where subtle ethical questions around issues of bias, transparency, and human creativity come into play.

The Stable Diffusion, DALL-E, MidJourney, and Deep Floyd IF are just a few among many of the AI image-generation models that have been taken seriously because of their remarkable ability to generate high-quality and imaginative visualizations from textual prompts [8]. These models depend on training datasets that often consist of a combination of open and closed data sources, thereby prompting concerns regarding intellectual property (IP) rights and transparency. While open-source models like Stable Diffusion encourage access and experimentation, closed-source models like MidJourney have their issues concerning transparency of the dataset and control over creative output. LAION-5B is one of the largest open-source image-text datasets used to train AI models for generating and understanding images. It contains over 5 billion image-text pairs scraped from the internet, helping AI models learn the relationships between words and visuals. The origin of training data, illustrated by LAION-5B, throws more light on ethical questions around the use of copyrighted material for the creation of AI art– hence enforcing the requirement of clear instructions on sourcing and

attribution in AI generated art. However, the opacity of the training set is also an issue – for example, LAION-5B, a widely used dataset, contains over 5 billion image-text pairs scraped from the web, which may include copyrighted content [6].

2.2 *Ethical Frameworks in Artificial Intelligence Art*

The issue of plagiarism in Al-generated art remains a contentious topic, given the unique nature of Al's creative processes. Traditional definitions of plagiarism, which involve copying or closely imitating someone else's work without attribution, become nuanced when applied to Al- generated art. AI models do not replicate existing works in a traditional sense but rather synthesize new images based on patterns learned from vast datasets, blurring the lines between originality and replication. As [20] observe, "AI systems reproduce elements from their training data in ways that defy traditional definitions of plagiarism." [20].

[11] found that "specific subject and style keywords increase coherence, while ambiguous prompts yield more creative but unpredictable results." Debates around Al as a tool versus an independent creator emphasize the questions of authorship in Al-generated artworks and the ownership of rights and creative autonomy.

2.3 *Ethical Implications and Legal Frameworks*

Integrating Al in the creation of artworks gives rise to deep ethical dilemmas, especially concerning authorship disputes, risks of plagiarism, and cultural impact related to AI-generated art.

AI models that can mimic or even surpass human-generated designs have raised serious concerns over the devaluation of traditional methods of art and the disturbance of established markets (Purdue Global Law School Blog). Regulatory frameworks such as the EU AI Act are ongoing attempts to rein in AI technologies, specifically in creative fields, thus putting more pressure on the updating of existing intellectual property laws in light of challenges raised by AI generated content (EU AI Act). These frameworks will explicitly establish regulations for the protection of artistic rights and promote ethical AI use within creative production.

2.4 *Key Theories and Debates*

The main theories in the debate around AI generated art are related to the essence of originality and authenticity of AI art, ethical concerns of using AI within the creative sectors, and legal concerns of IP and copyright related to AI generated materials. Scholars and practitioners are presently engaged in debates about the impact of AI on human creativity, the augmentation of self-expression via AI art tools, and the exploration of new artistic frontiers opened up by AI technologies. All these dialogues bring into sharp relief the need for ethical guidelines, legal certainty, and cultural sensitivity in responding to the interface between AI and art (IAPP.org).

3. METHODS

This study will develop an experimental design to check the originality of AI art by comparing different outputs produced with varied prompt formulations against existing artwork. Concretely, the study will focus on the analysis of similarities of AI generated images with pre-existing iconic paintings through structured variations in textual prompts. Three different prompts for each painting were used, with five outputs for each generated. This approach was replicated across three iconic paintings to account for variability in artistic styles, details, and interpretative possibilities. For each painting, three distinct prompt variations were used to generate five images per prompt, resulting in 45 AI generated outputs per painting (15 per prompt type). For the study we will be diving into the results of on such painting, however, all outputs will be available.

This design was intended to:

1. Capture variations in AI generated outputs based on different prompt formulations.
2. Assess whether including the artist's name, painting title, or stylistic restrictions influenced the similarity of the generated images to the original.
3. Quantify the level of similarity using computational distance metrics.

The experimental setup consisted of the following steps:

1. Selection of Paintings: Three iconic paintings were chosen for analysis. The chosen artworks spanned different artistic styles to ensure a diverse representation.
2. Prompt Variations: Three types of prompts were designed, differing in specificity and inclusion of references to the original artist and painting (detailed in Table 1).
3. Image Generation: AI generated images were produced using DALL-E, Stable Diffusion, and MidJourney, ensuring variability across different models.
4. Feature Extraction & Similarity Measurement: The generated images were compared to the original artworks using Bhattacharyya distance (to measure color distribution similarity) and Euclidean

distance (to measure feature vector similarity).

The prompts used in this study were structured into three categories as explained below and summarized in table 1:

1. Prompt with Artist's Name and General Description: This type of prompt explicitly referenced the original artist and provided a broad description of the subject matter (e.g., "Create a portrait of a woman with a serene expression in the style of Leonardo da Vinci").
2. Prompt without Artist's Name but with Detailed Description: This variation omitted the artist's name but included a detailed description of the subject and context to guide the AI's output (e.g., "Create a portrait of a woman with a serene expression, seated in a three-quarter pose, with hands resting gently together, wearing a dark dress, set against a tranquil landscape with diffused light").
3. Prompt with Painting Name and Artist, with Restrictions: This prompt referenced the original painting and artist but explicitly requested a reinterpretation rather than replication (e.g., "Create an inspired reinterpretation of the Mona Lisa by Leonardo da Vinci").

The purpose of these variations was to determine whether increased specificity in prompts influenced the degree of resemblance to the original paintings.

Table 1. A table summarizing the differences between all the prompts used to generate outputs from DALL-E

Prompt Type	Artist Name Included?	Painting Name Included?	Level of Description?	Example
Prompt 1: Artist & General Description	Yes	No	General Description	"Create a portrait of a woman with a serene expression and a slight, mysterious smile, seated against a blurred landscape background, in the style of Leonardo da Vinci."
Prompt 2: No Artist, Detailed	No	No	Highly Detailed	"Create a highly detailed portrait of a woman with a serene and enigmatic expression, her lips curled in a subtle, mysterious smile. She is seated in a poised, elegant posture, with her hands gently crossed in her lap. Her dark, soft hair falls in delicate curls, partly veiled by a translucent drapery, adding to her air of refinement."
Prompt 3: Direct Request & Restrictions	Yes	Yes	Moderate detail + reinterpretation n restriction	"Create the Mona Lisa inspired by Leonardo da Vinci"

To assess similarity, I analyzed the images using two primary methods:

1. Bhattacharyya distance measures the overlap between two probability distributions. In this study, it was used to compare the color distributions of AI generated images with those of the original artworks. A lower Bhattacharyya distance suggests greater similarity in color composition. A higher distance indicates more distinct color distributions.
2. Euclidean distance measures the straight-line distance between two points in a multi- dimensional space. Here, it was used to compare feature vectors extracted from the images using a pre-trained convolutional neural network. A lower Euclidean

distance indicates greater structural similarity. A higher distance suggests significant differences in composition.

4. RESULTS

4.1 Preliminary Observations of Prompt Outputs

1. Prompt 1: Artist & General Description
   "Create a portrait of a woman with a serene expression and a slight, mysterious smile, seated against a blurred landscape background, in the style of Leonardo da Vinci."
   Resulted in images that closely mimicked the Mona Lisa, with many AI generated versions retaining similar facial features and composition.
2. Prompt 2: No Artist, Detailed
   a. "Create a highly detailed portrait of a woman with a serene and enigmatic expression, her lips curled in a subtle, mysterious smile. She is seated in a poised, elegant posture, with her hands gently crossed in her lap. Her dark, soft hair falls in delicate curls, partly veiled by a translucent drapery, adding to her air of refinement."
   b. Produced more diverse interpretations, as the lack of an explicit artist reference encouraged AI to use broader stylistic choices.
3. Prompt 3: Direct Request with restrictions
   a. "Create the Mona Lisa inspired by Leonardo da Vinci"
   b. Resulted in reimagined versions, where stylistic elements were altered, but some core aspects of the original remained.

4.2 Similarity Computations

To quantitatively assess how similar AI generated outputs were to the original paintings, Bhattacharyya distance (color similarity) and Euclidean distance (structural similarity) were computed for each prompt.

Prompt 1

Figure 1. DALL-E generated images of the Mona Lisa using prompt 1 as listed in section 4.1, outputs 1 to 5 from left to right respectively

Figure 2. DALL-E generated images of the Mona Lisa using prompt 2 as listed in section 4.1, outputs 1 to 5 from left to right respectively.

Figure 3. DALL-E generated images of the Mona Lisa using prompt 3 as listed in section 4.1, outputs 1 to 5 from left to right respectively.

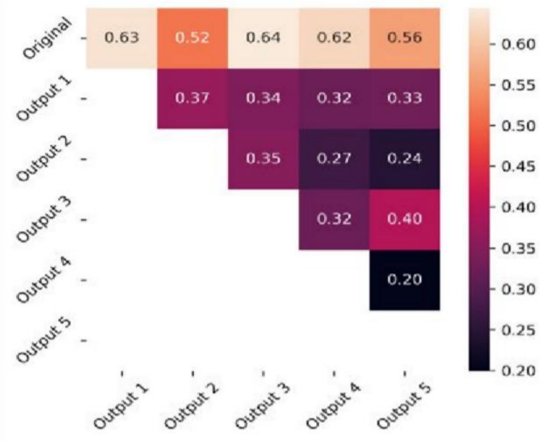

Figure 4. A heatmap of the Bhattacharyya distance scores for prompt 1 DALL-E generated images

As shown in figure 4 (which describes prompt 1 the outputs of which are shown in figure 1), the closest in color distribution is that of output 4 and output 5, with a value of 0.20, which means these two images have a very similar color composition. Generally, AI generated images have lower Bhattacharyya distance values compared to each other (greater similarity) than when compared to the original Mona Lisa, meaning they are more similar to each other than to the original artwork. For the DALL-E generated images, the distance ranges between 0.20 to 0.40, indicating that although there is color variation, the outputs have a generally similar style. When comparing the outputs to the original Mona Lisa, the Bhattacharyya distance values are the largest, lying in the range of 0.52 to 0.64, which indicates a high divergence in color distribution between the generated outputs and the actual painting.

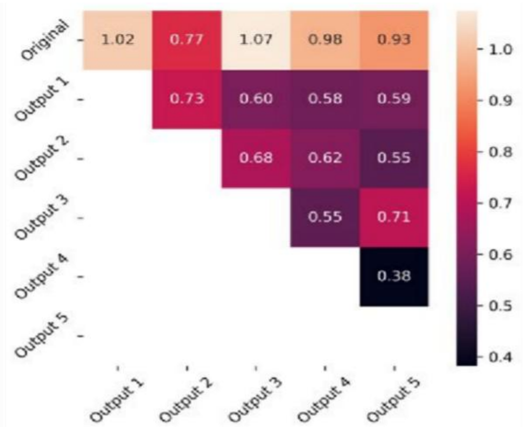

Figure 5. A heatmap of the Euclidean distance scores for prompt 1 DALL-E generated images

As shown in figure 5 (which describes prompt 1 the outputs of which are shown in figure 1), the largest value of color distribution similarity is between output 4 and output 5 (similar to the results of the Bhattacharyya distance), which is 0.38. The minimum Euclidean distance shows that these two images have highly similar structural compositions. The Euclidean distances among the different AI generated images are lower, ranging from 0.55 to 0.73, while their similarities to the original Mona Lisa range between 0.77 and 1.07. The highest Euclidean distance will be 1.07 between the original Mona Lisa and output 3, meaning this AI generated image differs most in structure compared to the original painting. Generally speaking, the original Mona Lisa always had a higher Euclidean distance value when compared to the DALL- E outputs; hence, the argument that such stylistically similar outputs are not perfect duplicates in structure and form keeps strengthening.

Prompt 2

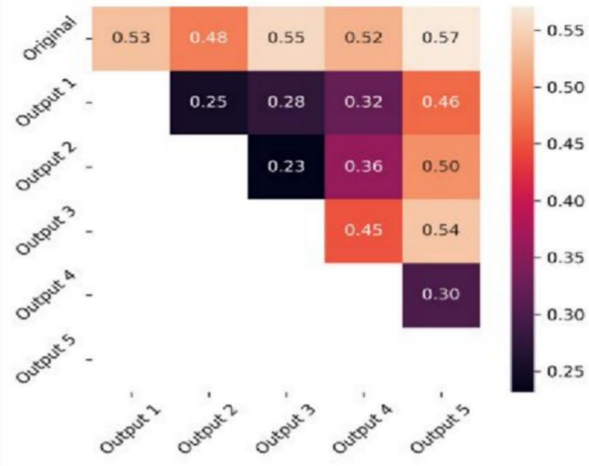

Figure 6. A heatmap of the Bhattacharyya distance scores for prompt 2 DALL-E generated images

As shown in figure 6 (which describes prompt 2 the outputs of which are shown in figure 2), the Bhattacharyya distance values for Prompt 2 range from 0.25 to 0.57, indicating moderate color divergence between the AI generated images and the original Mona Lisa. The closest match to the original Mona Lisa in terms of color similarity is output 2, which has the lowest Bhattacharyya distance (0.48), suggesting that its color distribution is the most aligned with the original painting. In contrast, output 5 has the highest Bhattacharyya distance (0.57), indicating that it deviates the most, from the original painting, in terms of color composition. Among the DALL-E outputs themselves, the Bhattacharyya distance values range from 0.23 to 0.54, showing that while there is variation, the outputs still share a significant degree of color similarity in comparison to that of the original painting. This pattern suggests that the AI model produces consistent color outputs with moderate variation.

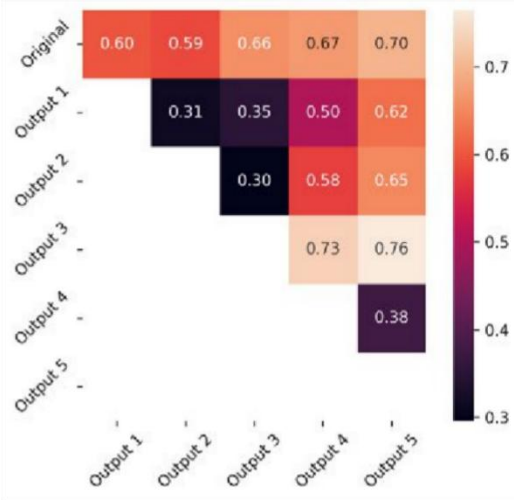

Figure 7. A heatmap of the Euclidean distance scores for prompt 2 DALL-E generated images

As shown in figure 7 (which describes prompt 3 the outputs of which are shown in figure 3), the Euclidean distance values for prompt 2 and the original Mona Lisa range from 0.59 to 0.70, signifying slight structural differences between the AI generated images and the original.

The most structurally similar image is output 2, with the lowest Euclidean distance, meaning it retains the closest resemblance to the spatial and form-related aspects of the original painting. Conversely, output 3 has the highest Euclidean distance, making it the most structurally different image from the original. Among DALL-E outputs, the Euclidean distance values range from 0.30 to 0.76, with some pairs being highly similar and others showing notable structural differences.

This variation suggests that while outputs maintain a degree of structural consistency, the model introduces enough diversity to create distinct yet recognizable variations of the Mona Lisa recreation.

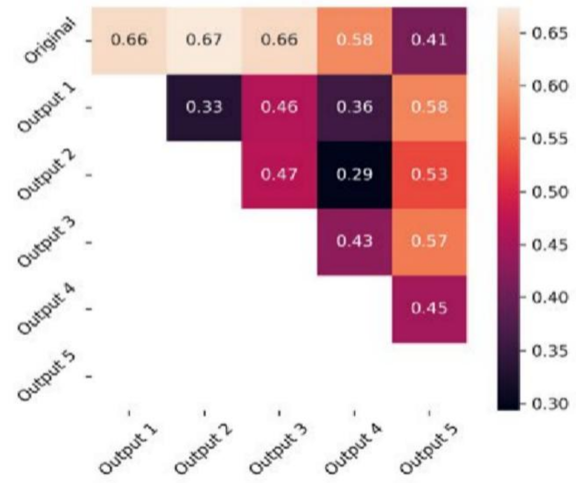

Figure 8. A heatmap of the Bhattacharyya distance scores for prompt 3 DALL-E generated images

As shown in figure 8 (which describes prompt 3 the outputs of which are shown in figure 3), the Bhattacharyya distance values of comparisons between the original Mona Lisa and the images generated using prompt 3 ranged from 0.41 to 0.67. The smallest Bhattacharyya distance was recorded between output 2 and output 4 which was 0.29, suggesting that these two images shared the most similar color distributions. The highest Bhattacharyya distance was found between output 1 and output 5 which was 0.58, indicating the largest difference in color distributions among the AI generated images. The highest value was for output 2, with a value of 0.67, which would indicate that it had the most significant deviation in color distribution from the original. The lowest Bhattacharyya distance was recorded for output 5, which was 0.41, indicating that this image retained the most similarity in color distribution with the original painting.

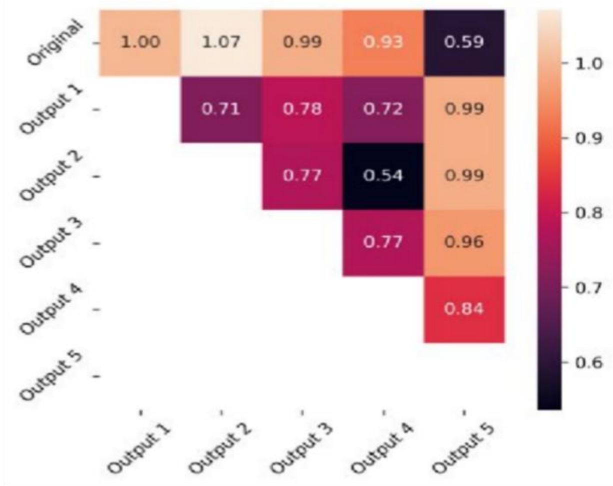

Figure 9. A heatmap of the Euclidean distance scores for prompt 3 DALL-E generated images

As shown in figure 9 (which describes prompt 3 the outputs of which are shown in figure 3), the Euclidean distance values ranged from 0.59 to 1.07 when comparing the outputs to the original. The most similar image pair in terms of Euclidean distance was output 2 and output 4 which was 0.54, confirming the trend observed in the Bhattacharyya distance analysis. The most distinct image pair was output 1 and output 5, which had the highest Euclidean distance (0.99), signifying notable differences in pixel composition and structural features. The image with the greatest Euclidean distance from the original was output 2 with 1.07, signifying that it had the most substantial structural and pixel-based differences. Conversely, output 5 had the lowest Euclidean distance 0.59, reinforcing that this image preserved the most structural similarity to the original Mona Lisa. These findings align with the Bhattacharyya distance results, suggesting that output 5 is the closest representation of the original, while output 2 shows the most significant variation.

4.3 Discussion and Conclusion

This study set out to explore a surprisingly tricky question: just how original is AI generated art when it's asked to recreate something as known as the Mona Lisa? By using the similarity metrics Bhattacharyya and Euclidean distance, I was able to get a clearer picture of how closely AI generated images align with the original–and how much the specific wording of a prompt can shape the accuracy of the final output.

What stood out most to me was the consistency within the DALL-E's own outputs. In accordance to the prompts, the images it generated tended to look more like each other than they did like the actual painting. That pattern suggests that AI models draw heavily from the visual patterns they've learned during the training phase, rather than aiming to replicate specific reference works exactly. In fact, when I was coming up with prompts to utilize in this study I originally requested for a direct replication of paintings. However, the AI refused due to ethical concerns, demonstrating the built-in guardrails designed to uphold ethical standards.

Interestingly, regardless of the prompt used for the art regeneration, the average of the Bhattacharyya and Euclidean distance for each prompt compared to the original painting were around the same with slight variation. As follows:

1. Prompt 1:
    a. Bhattacharyya distance: 0.594
    b. Euclidean distance: 0.954
2. Prompt 2:
    a. Bhattacharyya distance: 0.594
    b. Euclidean distance: 0.644
3. Prompt 3:
    a. Bhattacharyya distance: 0.596
    b. Euclidean distance: 0.916

In contrast, prompts that were more open-ended or abstract, especially those that asked the model to "reinterpret" the Mona Lisa, led to results that looked noticeably different. It was fascinating to see how something as seemingly small as including or leaving out a name can shift the direction of the artwork so dramatically.

These findings contribute to the broader discussion around originality and authorship in AI generated art. None of the generated images were exact copies of the original, but some came close enough to raise valid ethical questions. Is an image still considered "original" if it mimics the tone, structure, and emotional feel of a centuries-old masterpiece? At what point does inspiration cross the line into imitation? While the AI clearly isn't copying in a literal, pixel-for- pixel sense, its outputs are undeniably influenced by what it's been exposed to. That gray area is exactly where future conversations around policy and ethics should focus their attention.

If I were to run this experiment again, there are definitely a few things I'd approach differently. First, I'd expand the scope beyond just the Mona Lisa. It would provide great insights to explore how AI responds to prompts involving artworks from other periods or movements, say, something by Picasso or Monet. I'd also like to include outputs from a wider range of AI platforms. This study primarily focused on DALL-E, but bringing in tools like MidJourney or Stable Diffusion would offer a more well-rounded view of how different models interpret similar instructions. Finally, I think there's real value in adding a human element to the analysis–maybe through a survey asking people how "original" or "familiar" the images feel to them. Sometimes, people's perceptions can tell us just as much, if not more, than numerical metrics can.

In the end, this study helped me see that AI generated art exists in a space between imitation and creation. It doesn't simply copy what already exists: it reshapes, reinterprets, and reimagines, depending on how we guide it. That's part of what makes it so exciting, but also what makes it ethically complex. As these technologies continue to evolve, we're going to need to keep asking tough questions about authorship, originality, and where creativity truly begins. My hope is that this research adds something meaningful to that ongoing conversation.

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