International Journal of Multidisciplinary Studies and Innovative Technologies

IJMSIT

e-ISSN: 2602-4888 | 2025, 9 (1), 102-107
dergipark.org.tr/en/pub/ijmsit | DOI: 10.36287/ijmsit.9.1.14
Research Article | Received: June 24, 2025; Accepted: July 17, 2025

Plotting of Generative AI-Images via Low-Cost Robotic Arm

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Abstract – This study proposes an AI-driven system that integrates generative artificial intelligence with robotic arm to create and physically render visual content. Utilizing state-of-the-art text-to-image models, the system first generates high-resolution images based on natural language prompts. These images are then processed and translated into vector paths suitable for robotic execution. A robotic arm, specifically the BrachioGraph platform, is employed to draw the generated content on a physical medium, effectively bridging the gap between digital generation and tangible realization. The system architecture combines deep learning-based image synthesis, path optimization algorithms, and precise robotic control. Although the study has certain optimization errors that cause vibration because it was created with Raspberry Pi and simple equipments, it is a prototype study that shows that artistic studies can be created by AI technologies.This interdisciplinary approach demonstrates a novel pipeline where AI-generated creativity is physically manifested through robotics, opening new possibilities in automated content creation, human-machine collaboration, and AI-driven artistic expression.

Keywords *– BrachioGraph, Generative AI, Robotic Arm, Image Plotting, Human-Machine Interaction*

Citation: Yayla, R., (2025). Physical Rendering of AI-Generated Images via Low-Cost Robotic Arm. International Journal of Multidisciplinary Studies and Innovative Technologies, 9(1): 102-107.

I. Introduction

In recent years, artificial intelligence (AI) technologies have advanced rapidly, transforming various fields such as healthcare, education, and entertainment. One of the most exciting developments is the ability of AI to generate realistic and creative images from simple text prompts. These AI-generated images are typically viewed on digital screens, when these images brought into the physical world as hand-drawn artworks, the images can more valuable artworks for art world.

This study basically explores the combination of AI-generated art with robotic technology to create a system that can draw these images on paper. The system takes AI-generated visuals and translates them into precise pen strokes by using a simple robotic arm based on the BrachioGraph platform. The main goal is to bridge the gap between digital creativity and physical representation, making AI art more interactive and tangible.

The system is designed to be user-friendly, with a graphical interface that allows users to input text prompts, preview the AI-generated image, and initiate the drawing process. By automating the transition from digital art to physical sketches, this project highlights the potential of AI and robotics in creative applications, offering new possibilities for artists, educators, and hobbyists alike.

II. Materials and Method

A. Literature Review

In today, there are a lot of literature studies based on generative AI-images and robotic separately. The aim of this study is to present a basic method that combines generative artificial intelligence studies with a low-cost robotic arm design. In artistic activities, the use of generative artificial intelligence also brings with it some differences. Dheenadhayalan et al. explored the operational mechanisms of contemporary AI-based art generators and highlighted a range of challenges these systems face from technical, ethical, and legal perspectives. [1]. Göring and colleagues conducted a crowdsourced evaluation to assess the visual quality and appeal of images generated by AI, extending the AVT-AI-Image dataset for this purpose. [2]. Song et al. analyzed how models equipped with image-to-text functionality—such as CLIP (ViT-L and ViT-H), DeepDanbooru, GPT-4, and Gemini 1.5 Pro—can be utilized to automatically generate prompts aimed at producing high-quality single-character images, thereby facilitating the ideation process for character creation. [3]. Zambroba and collaborators investigated the use of text-to-image artificial intelligence models for generating synthetic images, with the objective of improving the precision and overall performance of image classification systems. [4]. Fu introduced an intelligent classification system that leverages big data analytics, AI technologies, and a closed-loop control framework to assist users in sorting waste efficiently. [5]. Megalingam et al. designed and evaluated a prototype of a miniature robotic controller arm, which employs Bluetooth wireless communication to manually operate a robotic arm featuring three degrees of freedom. [6]. Diaz and his team proposed integrating a Lynxmotion AL5 robotic arm, capable of five degrees of freedom, with the FESTO-developed mobile robotic platform Robotino, using a Raspberry Pi 4 as the control interface. [7]. Similar to our study, Bidgoli et al. proposed a method to integrate an artistic style to the brushstrokes and the painting process through collaboration with a human artist. They conducted their work in three stages: 1) collecting brush strokes and hand brush movement samples from an artist, 2) training a generative model to generate brush strokes of the artist's style, and 3) fine-tuning a stroke-based rendering model to work in a robotic painting setup [8].

B. System Overview

The plotting system contains three steps as AI-image generation, vectorization and path planning and finally robotic arm plotting for AI-image plotting. Current models based on generation AI-image is usually used by API based on different AI platforms. Another solution is also local models created by training in local computer. There is no any differences in these models. The models are the same AI-model but the basic differences is in training process. While the AI-image is created by local models in many hours (according to the image complexity) with personal desktop or laptop hardware, AI-image based on API can be created in a few seconds with its efficient hardware such as GPU, CPU and disk memory. In this study, API is used for faster in AI-image generation.

The second step is to introduce the AI image created in png format to the robotic arm and make it suitable. For this process, the AI image created in png format must be vectorized to be compatible with point strokes.

The final step is to plot of the vectorized AI-image by robotic arm. The completion of this process may vary depending on the complexity of the vectorized AI image. In addition, the power supply of the created robotic arm is another important issue for the completion of the process.

C. Hardware Components

The system's hardware components are shown in Figure 1. The robotic arm is built using a 3-servo BrachioGraph design (shoulder, elbow, and pen-lift mechanisms) constructed from lightweight and affordable materials [9]. The main components include:

- A Raspberry Pi 3 Model B serving as the control unit, generating PWM signals to precisely control three Micro Servo Motors SG90
- The arm structure assembled using popsicle sticks for the linkages
- A bamboo clothes peg modified to hold a standard pilot pen as the drawing tool
- Silicon adhesive used to securely mount the servo motors to the popsicle stick frame

The mechanical design prioritizes stability and precision while maintaining simplicity. The bamboo clothes peg

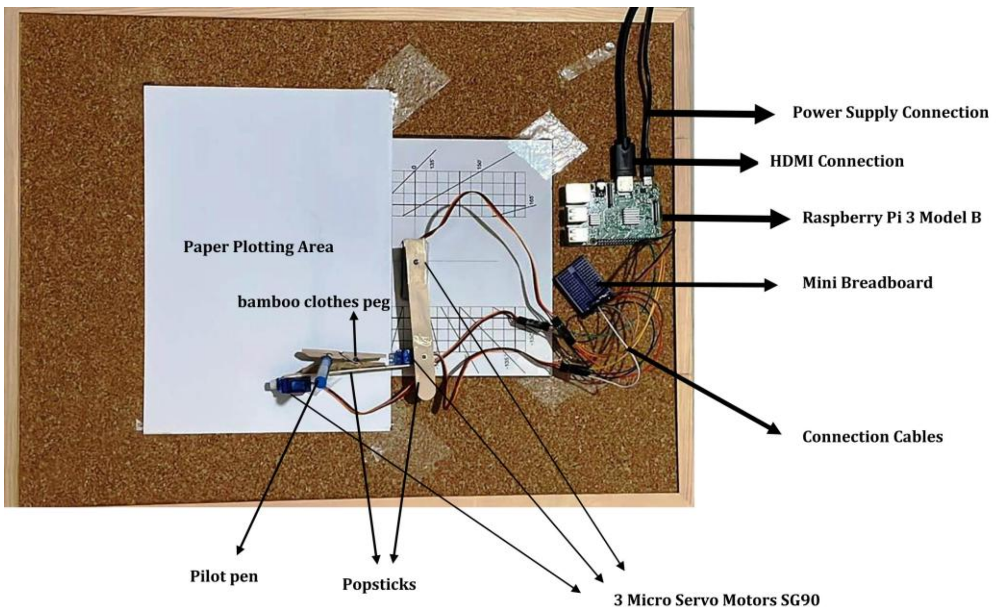

Fig. 1. Robotic Arm Plotting Components

provides a reliable mechanism for holding and releasing the Pilot pen during operation. Silicon adhesive was chosen to firmly attach the servo motors to the popsicle stick structure, ensuring minimal vibration during movement. The lightweight construction allows the SG90 servos to operate efficiently within their torque limits [10]. This combination of readily available components, all visible in Figure 1, demonstrates an effective and economical approach to robotic arm construction.

D. Software Components

The system features a Tkinter-based GUI (Graphical User Interface) that allows users to input text descriptions of desired images through a dedicated text field. These prompts are processed via the DreamStudio API to generate AI images, which are then displayed as previews within the interface. The GUI includes functional buttons for saving images, initiating vectorization (using OpenCV and Potrace to convert raster images to SVG paths), pen lifting/lowering controls, and executing the drawing process. For robotic control, Python scripts (utilizing RPi.GPIO and pigpio libraries) translate the vectorized paths into precise PWM signals that coordinate the servo movements of the robotic arm. This integrated software architecture enables seamless transition from text input to physical drawing execution.

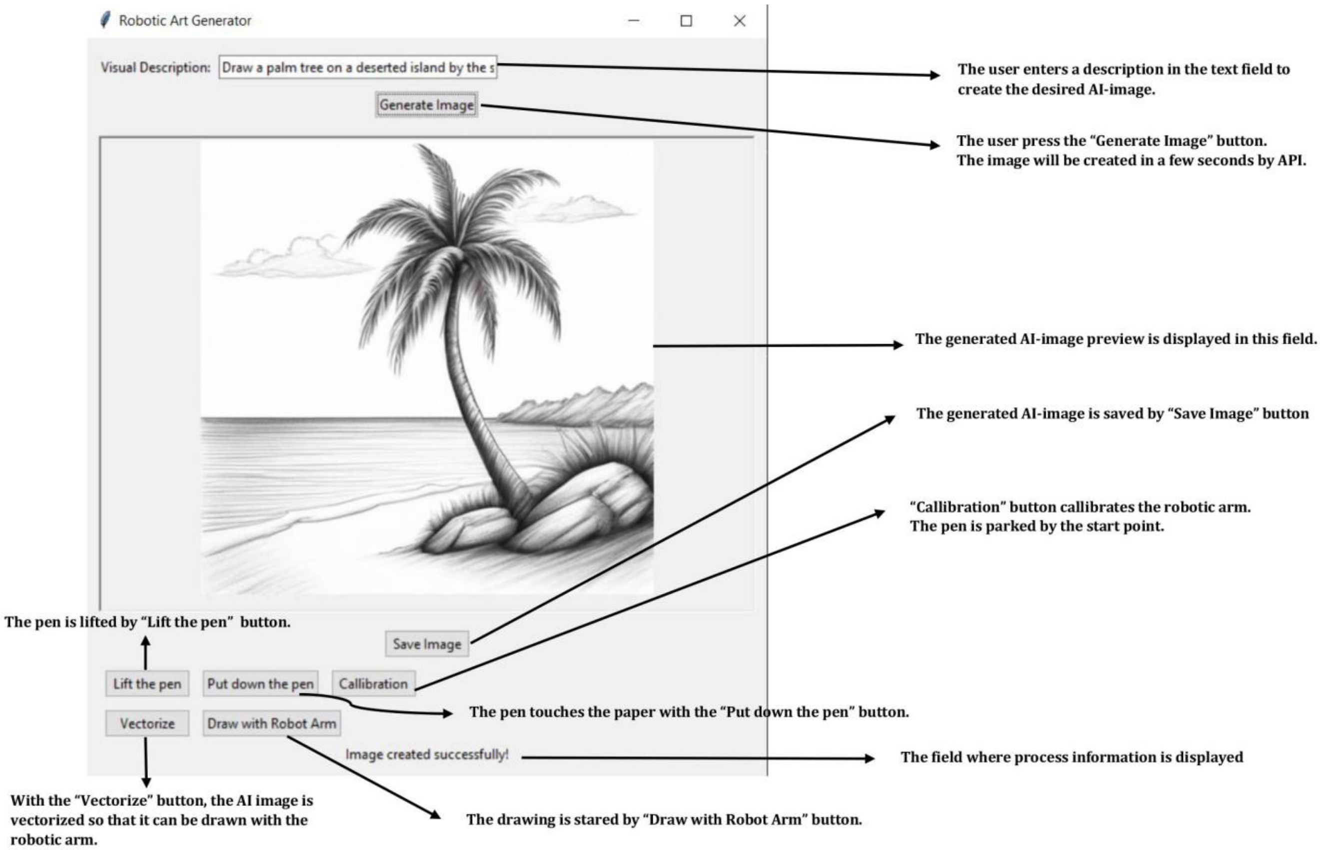

Fig. 2. Tkinter GUI structure and descriptions

The Tkinter-based GUI is shown in Figure 2. Initially, the user enter the description of AI-image to text field. Secondly, once the user clicks the "generate image" button, the AI image is generated within seconds via the DreamStudio API [11]. Since DreamStudio API is an official service offered by Stability AI, it generally uses the most up-to-date and optimized Stable Diffusion models [12]. Another method of creating an AI image is to download the Stable Diffusion model to the local computer and use it, but in this method, the generation of the AI image may take hours depending on the local hardware configuration. . Since the AI image can be created quickly, the dreamStudio API is used in this study to generate the AI image. In addition, the dreamstudio service gives its first users a certain number of free credits for AI image generation. The desired AI image can be gray scale or colorful. However, when the user clicks the "Save Image" button and saves the image, then clicks the "Vectorize" button, the generated AI image is converted to black and white vectors in any case for drawing with robotic arm. A sample generated image and vectorized image have been shown in Figure 3.

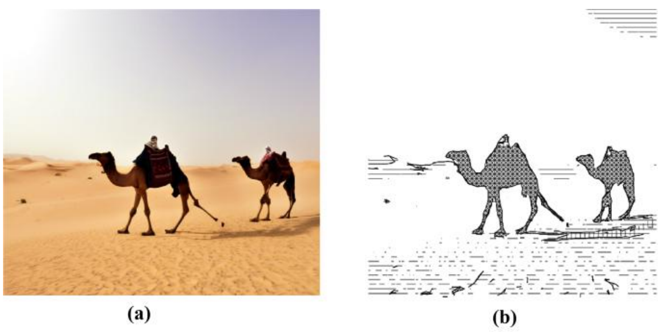

Fig. 3. (a) Generative AI image (b) Vectorized Image for drawing

In addition, the "Lift the pen" button is used to attach the pen to the robotic arm, the "Put down the pen" button is used to touch the paper, the "callibration" button is used to calibrate the robotic arm and finally the "Draw with Robot Arm" button is used to start drawing. Drawing duration may vary depending on the power given to the Raspberry Pi and the complexity of the vectorized image.

E. Advantages and Challanges

Prompt engineering represents one of the fastest and most accessible methods for generating AI-based artwork within the field of artificial intelligence. Users can effortlessly input textual descriptions of their desired images, which are then synthesized by pre-trained generative models such as Stable Diffusion, DALL·E 2/3, Imagen, or various GAN-based architectures [13-15]. One of the key advantages of this approach is its cost-effectiveness; the system can be implemented using low-cost hardware components, and the setup process is relatively straightforward due to its structured and modular design.

However, despite these benefits, several limitations are associated with the use of such low-cost robotic systems for physical image rendering. Vibrational movements produced by servo motors may lead to misalignments and inaccuracies in the drawing process. Furthermore, improper attachment of the pen—such as insecure placement in a bamboo clothes peg—or the lack of initial calibration can similarly result in drawing errors. These limitations highlight the inherent trade-offs in utilizing low-cost robotic arms for AI-generated image plotting. The calibration problems cause vertical and horizontal draw problems. This problem give rise not to draw a clear image. Calibration must be done very well before drawing. However, a clear drawing cannot be made due to the vibration movements of servo motors. Instead, better equipment is needed.

III. Experimental Results

A. Accuracy Analysis

The Structural Similarity Index (SSIM) is a widely used perceptual metric that measures the similarity between two images [16]. Unlike traditional metrics such as Mean Squared Error (MSE) or Peak Signal-to-Noise Ratio (PSNR), SSIM considers changes in structural information, luminance, and contrast. It better aligns with human visual perception by evaluating image degradation based on perceived changes rather than absolute pixel differences.

Mathematically, SSIM compares local patterns of pixel intensities that have been normalized for luminance and contrast [17]. The output score ranges from -1 to 1, where a value of 1.0 indicates perfect structural similarity between the two images. This makes SSIM particularly suitable for applications where visual similarity is more important than raw pixel accuracy, such as image generation, compression, and robotic reproduction.

In this study, SSIM has been used to quantitatively assess the visual similarity between the AI-generated image and the robotically rendered drawing. The comparison has been performed using a grayscale preprocessing step, followed by

Fig. 3. The Generated Image, Robotic Drawing and Similarity Map of Sample 1

Fig. 4. The Generated Image, Robotic Drawing and Similarity Map for Sample 3

image resizing to ensure consistent dimensions. The structural_similarity function from the skimage.metrics library has been employed to compute both the SSIM score and the corresponding difference image [17-18].

A difference image map has been generated, where each pixel's value represents the local similarity score to enhance the interpretability of the comparison. In addition, matching regions—where the structural similarity has been above a defined threshold—were highlighted in green. This visual overlay enabled a more intuitive understanding of which regions of the robotic drawing closely matched the original generated image.

B. Findings

The SSIM-based evaluation provides both a quantitative metric (e.g., a similarity score of 0.85 or 85%) and a qualitative visualization of the differences and similarities [19]. This dual analysis has helped confirm that the robotic arm reproduced key structural elements of the original AI-generated image with an average degree of fidelity. Regions with high correspondence have been shown prominently in green on the SSIM difference map, demonstrating that the robotic drawing has preserved critical visual features.

In combination with other evaluation metrics such as MSE, PSNR, and histogram correlation, the SSIM analysis contributed a comprehensive assessment of drawing accuracy from both pixel-based and perceptual standpoints [20].

In this section, a detailed analysis table based on a few samples drawn by the robotic arm has been shown in Table 1.

Table 1. Similarity Reports for samples

Sample	Structural Similarity Index (SSIM)	Mean Squared Error (Normalized)	Peak Signal-to-Noise Ratio (PSNR)	Histogram Correlation Similarity
Sample 1	0.0204 (2.04%)	0.69 %	1.61 dB	-0.0103
Sample 2	0.5026	0.1173 %	9.31 dB	0.0166
Sample 3	0.4693	0.1456%	8.37 dB	-0.0071

According to the experimental results, the reason for the higher MAE value depends on the background colour and scanning problem of the white paper in sample 1. While sample 1 has a higher error value due to the white background problem, this error is minimized in sample 2 and sample 3 because it has a white background. On the other hand, the calibration problems of the servo motors are the biggest challenges for the platform. In this study, simple types of equipment are used for creating a robotic arm such as bamboo clothes pegs, connecting cables, and popsticks. If the step motors had been used for rotations, the drawings should have become more accurate.

IV. Results

The implemented system successfully demonstrated the ability to transform text-based prompts into visual artwork using a robotic arm. High-resolution images generated by state-of-the-art text-to-image models were effectively converted into vector paths and translated into robotic motion through the BrachioGraph platform. The robotic arm was able to draw simplified representations of the generated images on physical media, validating the system's capacity to bridge digital generation and tangible output.

Despite hardware limitations—including minor vibrations and calibration drift due to the use of a Raspberry Pi 3 Model B and basic servo motors—the prototype consistently produced recognizable drawings [21]. Visual comparisons between the original AI-generated images and the robotic renderings were evaluated using image similarity metrics such as SSIM, MSE, PSNR, and histogram correlation. Results indicated moderate structural accuracy and acceptable perceptual quality, supporting the feasibility of the method for physical rendering.

Furthermore, the system demonstrated that the complexity of the prompt directly affected the drawing quality: simpler compositions with well-separated features resulted in clearer and more accurate robotic outputs. This finding underscores the importance of prompt engineering and image preprocessing in such hybrid AI-robotic systems.

Overall, this prototype proved the idea that AI can help make real artworks and serves as a starting point for future projects. In future studies, more complex robotic arm design can be created and the calibration problems can be minimized for drawing tasks.

V. DISCUSSION

This study shows that generative AI can be effectively combined with low-cost robotic systems to create physical artworks from text prompts. While the results are promising, the use of basic hardware like a Raspberry Pi and simple servo motors introduced issues such as minor vibrations and calibration errors, leading to overlapping or inaccurate lines. Despite these limitations, the system successfully demonstrated the concept of AI-driven physical art creation and highlighted its accessibility for educational and experimental purposes. Future improvements in hardware precision, path optimization, and feedback mechanisms could enhance output quality and broaden the system's creative potential.

VI. CONCLUSION

This prototype study has shown that generative AI and low-cost robotic systems can be successfully integrated to create physical artworks based on natural language prompts. Despite hardware limitations affecting precision, the system effectively demonstrates the potential for AI-driven artistic expression in tangible form. The project lays a foundational step toward more advanced, creative human-machine collaborations and highlights new possibilities for automated art creation in both educational and experimental contexts.

Acknowledgment

The author(s) thank to DreamStudio AI Platform for free credit of generative API and Kevin McAleer for providing the Branciograph-based robotic arm construction instructions.

Authors' Contributions

The authors' contributions to the paper are equal.

Statement of Conflicts of Interest

There is no conflict of interest between the authors.

Statement of Research and Publication Ethics

The authors declare that this study complies with Research and Publication Ethics

REFERENCES

[1] K. Dheenadhayalan et al., "AI Art Generators: Human Creativity Vs Artificial Intelligence," in Proc. 2024 Int. Conf. Power, Energy, Control and Transmission Systems (ICPECTS), IEEE, 2024.

[2] S. Göring, R. R. Ramachandra Rao, R. Merten, and A. Raake, "Appeal and quality assessment for AI-generated images," in Proc. 15th Int. Conf. Quality of Multimedia Experience (QoMEX), Ghent, Belgium, 2023, pp. 115–118.

[3] S. Song, J. Song, J. Lee, Y. Kang, and H. Moon, "Exploring the potential of novel image-to-text generators as prompt engineers for CivitAI models," in Proc. 16th IIAI Int. Congr. Advanced Applied Informatics (IIAI-AAI), Takamatsu, Japan, 2024, pp. 626–631.

[4] O. Zambrano and B. Senouci, "Image classification improvement: Text-to-image AI for synthetic dataset approach," in *Proc. 49th Euromicro Conf. Software Eng. and Advanced Applications (SEAA)*, Durres, Albania, 2023, pp. 74–77.

[5] L. Fu, "Research on the construction system of computer big data in the community integrated garbage classification AI image recognition platform," in *Proc. IEEE Conf. Telecommunications, Optics and Computer Science (TOCS)*, Dalian, China, 2022, pp. 643–647.

[6] R. K. Megalingam, S. Boddupalli, and K. G. S. Apuroop, "Robotic arm control through mimicking of miniature robotic arm," in Proc. 4th Int. Conf. Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2017, pp. 1–7.

[7] B. Díaz, N. Pacheco, and L. Vinces, "Integration of a robotic arm Lynxmotion to a Robotino Festo through a Raspberry Pi 4," in Proc. IEEE Int. Conf. Automation / XXV Congr. Chilean Assoc. Automatic Control (ICA-ACCA), Curicó, Chile, 2022, pp. 1–5.

[8] A. Bidgoli, M. L. De Guevara, C. Hsiung, J. Oh, and E. Kang, "Artistic style in robotic painting; a machine learning approach to learning brushstroke from human artists," in *Proc. 29th IEEE Int. Conf. Robot and Human Interactive Communication (RO-MAN)*, Naples, Italy, 2020, pp. 412–418.

[9] K. McAleer, *BrachioGraph*, Kev's Robots, Jul. 26, 2024. [Online]. Available: https://www.kevsrobots.com/blog/brachiograph.html [Accessed: Jan. 8, 2025].

[10] *SG90 Datasheet*. [Online]. Available: http://www.ee.ic.ac.uk/pcheung/teaching/DE1_EE/stores/sg90_datasheet.pdf [Accessed: Mar. 7, 2025].

[11] Stability AI, "DreamStudio API," *Stability AI Developer Platform*, Accessed: Apr 22, 2025. [Online]. Available: https://platform.stability.ai/docs/api-reference

[12] *Stable Diffusion Art - Models*. [Online]. Available: https://stable-diffusion-art.com/models/ [Accessed: Feb 05, 2025].

[13] S. Jamal, H. Wimmer, and C. M. Rebman Jr., "Perception and evaluation of text-to-image generative AI models: A comparative study of DALL-E, Google Imagen, GROK, and Stable Diffusion," *Issues in Information Systems*, vol. 25, no. 2, pp. 277–292, 2024.

[14] C. Zhang, C. Zhang, M. Zhang, and I. S. Kweon, "Text-to-image diffusion models in generative AI: A survey," *Journal of LaTeX Class Files*, vol. 14, no. 8, pp. 1–20, Aug. 2015.

[15] M. Kang, J.-Y. Zhu, R. Zhang, J. Park, E. Shechtman, S. Paris, and T. Park, "Scaling up GANs for text-to-image synthesis," *arXiv preprint arXiv:2303.05511*, Mar. 2023. [Online]. Available: https://arxiv.org/abs/2303.05511

[16] Z. Wang, A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," *IEEE Transactions on Image Processing*, vol. 13, no. 4, pp. 600–612, Apr. 2004.

[17] A. Sciarra, S. Chatterjee, M. Dünnwald, G. Placidi, A. Nürnberger, O. Speck, and S. Oeltze-Jafra, "Automated SSIM Regression for Detection and Quantification of Motion Artefacts in Brain MR Images," *arXiv preprint arXiv:2206.06725*, Jun. 2022. [Online]. Available: https://arxiv.org/abs/2206.06725

[18] A. Hore and D. Ziou, "Image quality metrics: PSNR vs. SSIM," in *Proc. 20th International Conference on Pattern Recognition (ICPR)*, Istanbul, Turkey, Aug. 2010, pp. 2366–2369.

[19] G. Prieto Renieblas, A. Turrero Nogués, A. Muñoz González, N. Gómez-Leon, and E. Guibelalde del Castillo, "Structural similarity index family for image quality assessment in radiological images," *Journal of Medical Imaging*, vol. 4, no. 3, p. 035501, Jul. 2017.

[20] U. Sara, M. Akter, and M. S. Uddin, "Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study," *Journal of Computer and Communications*, vol. 7, no. 3, pp. 8–18, Mar. 2019. https://doi.org/10.4236/jcc.2019.73002

[21] T. Bayrak *et al*., "Raspberry Pi based Object Detection and Drawing," in *Proc. Global Conf. on Engineering Research (GLOBCER'21)*, Balıkesir, Turkey, 2021, pp. 194–201.