Enhancing the Traditional Batik Design Practices: An Approach to Batik Motif Design Using Artificial Intelligence

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Abstract— **The development of hand-drawn batik motifs has decreased significantly as well and many motifs have not been documented. This research presents artificial intelligence generative approach to increase variance in the domain of Bakaran batik motifs. This research introduces three different versions of the Stable Diffusion algorithm: Version 1.5, Version 2.0, and SDXL. This study explores the capabilities of Stable Diffusion in generating Bakaran batik motifs. The study concludes that Version 1.5 and SDXL are the most effective models, each with unique strengths and trade-offs. SDXL is ideal for artists seeking to push the boundaries of traditional batik design, while Version 1.5 preserves traditional patterns and ensures cultural authenticity. Evaluation using VGG-11 supports SDXL's superior performance in generating batik patterns, whereas Version 2.0 consistently underperforms across all metrics. This research demonstrates the versatility of the Stable Diffusion with LoRA technique when applied to batik motif. By combining deep learning methods with batik motifs, our findings open up new opportunities in the convergence of artistic creativity and technological innovation. This study may help to increase the productivity of batik industry players, especially workflow trimming at the ideation stage.**

Index Terms— **Generative AI, Text-to-image, Traditional batik, Deep learning, Culture, Heritage, Stable Diffusion.**

I. Introduction

Indonesian batik is included in the list of cultural heritage representatives as Masterpieces of the Oral and Intangible Heritage of Humanity by UNESCO [1]. The rich tapestry of traditional artistry is a testament to the human spirit's enduring creativity and cultural heritage [2]. In batik motif design, where centuries-old traditions intertwine with artistic expression, preserving this cultural legacy is paramount [3]. The motifs that have been carefully crafted and passed down through generations represent a unique and irreplaceable repository of cultural history. However, the preservation of traditional batik motifs have entered an alarming stage due to the difficulty of regenerating batik makers. Young people's lack of interest in pursuing batik has an unfavorable impact on this industry [4]. Many original motifs from batik designers are lost without being digitized due to manual drawing techniques. And the loss of the legacy of the traditional batik motif that has been passed down from generation to generation in various batik-producing regions in Indonesia.

Technology to assist batik actors in producing motifs for modern batik is essential today due to the large client demand and demand for motif designs. The batik makers on the coast, such as batik Bakaran, still make their batik by drawing manually, especially with nature motifs such as animal and floral. Techniques for digitising batik design have been developed for many years. D-batik [5] and Fractal Batik utilize a computational program to reduce production time [6]. Similarly, image processing is also utilized for batik digitalization [7]. This greatly impacts the duplication of motifs and speeds up pattern ideas in batik design. However, the output of fractal batik is not dynamic and is repetitive because it is based on geometry. Moreover, Surahman et al. (2023) define two primary processes in using computational programs for producing batik prints. The first process is designing the pattern using program, and the second is printing the batik using IoT [8]. In other words, if the batik is produced using traditional means, only the first process will be used. In this research, only the first process will be evaluated for traditional batik techniques which uses handdrawn method. The use of generative AI will be explored to generate new batik pattern [9-11].

Furthermore, deep learning to classify the authenticity of batik using the Convolutional Neural Network has been attempted to digitize batik motifs so they do not disappear [12]. Although the artificial intelligence model shows promising results in classifying batik images, the very diverse batik motifs require regular updates in the database [13]. The AI form used is the Generative adversarial network to generate the batik [14]. While the model aims to remove blocking artifacts, it may still face difficulties handling more intricate or subtle artifacts that can occur in Batik patterns. Further refinement in artifact removal is needed.

Our study proposes to bridge tradition and innovation by employing generative deep learning techniques to enhance batik motif design. This study introduces three distinct

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versions of the Stable Diffusion algorithm, specifically V1.5, V2.0, and the pioneering SDXL (Stable Diffusion eXtended learning) [15-17], to explore their potential in generating a diverse range of batik motifs, particularly those inspired by the wonders of the natural world since most of the batik motifs depict floral or animals. Version 1.5, in a trimmed-down form, represents an established iteration of the Stable Diffusion framework. This framework has undergone refinements and optimizations, making it a reliable choice for creative applications. Version 2.1, on the other hand, embodies the evolution of this framework, incorporating improvements and advancements that make it a strong contender for generating intricate patterns and designs. Finally, SDXL, a new extension of StableDiffusion, promises innovation and has the potential to revolutionize generative artistry through its extended learning capabilities.

The comparison of stable diffusion versions is crucial for the creation of batik motifs due to its potential impact on the preservation and evolution of traditional motifs, as well as the development of new designs. The use of stable diffusion V1.5, V2.1, and SDXL in creating batik motifs is essential as it allows for the exploration of geometric concepts, mathematical equations, and the implementation of art and technology in motif design [18]. Additionally, the comparison of stable diffusion versions can contribute to the modernization of batik designs, making them more accessible for educational purposes and engaging students in cultural heritage [19]. The comparison of stable diffusion versions is crucial for understanding the intricate processes involved in motif creation, preserving cultural heritage, and fostering innovation in the realm of batik motifs [20].

Although the promise of AI in creative fields often raises concerns about the displacement of human expertise and craftsmanship, it is crucial to emphasize that our research does not aim to replace skilled batik workers and designers who have been the custodians of this intricate art form for generations. Instead, this research aims to complement their expertise and preserve the traditional motifs passed down through the ages. Rich in history and culture, these motifs are unique at the heart of batik artistry. Therefore, our research seeks to reinvigorate the design process of Batik motifs and ensure the sustainability of these traditional motifs. Generating batik motifs through stable diffusion is expected to be a solution to digitize batik design assets in each region while developing modern batik motifs to increase productivity and reduce batik design production time. On the other hand, this research can bring economic development to the batik industry.

II. Method

To find the best-performing Stable Diffusion model in generating batik pattern, we used two quantitative methods, mainly in generative models: inception score and CLIP score [21]. The inception score determines the variability amongst generated images, while the Contrastive Language-Image Pre-Training (CLIP) score ensures the generated images are closely related to the given captions [22]. Thus, our methods are as follows:

A. Determine the generative model

We have judiciously curated three distinct iterations within the Stable Diffusion framework to identify the most appropriate generative model for our research. These models encompass the refined Version 1.5, the advanced Version 2.1, and the pioneering Stable Diffusion Extended Learning (SDXL). Our choice of these models is intricately grounded in their pronounced significance and eminence within the intricate domain of generative deep learning**.**

B. Determine the input prompt

Each model will generate eight images using five different prompts. Each prompt consists of a static prompt defining the main objective of the generated images and a varying prompt indicating an object generally found in a batik pattern. We used a different random seed for each prompt to differentiate the produced pattern since the varying prompts only occupy one positional prompt (compared with three positions for the static prompt). This method ensures that even though given the same weights, the generated images for each prompt do not have overlapping patterns. Then, the base prompt and the varying prompt will be used as the input of each generative model. For example, the first prompt will be "batik pattern, black and white, sketch, komodo" with random seed of 20. No negative prompt was used. The complete list of prompts can be seen in Table I.

TABLE I
THE DETAILS OF THE INPUT PROMPT

Seed	Base Prompt	Varying Prompt
20	batik pattern, black and white, sketch,	komodo
30	batik pattern, black and white, sketch,	butterfly
40	batik pattern, black and white, sketch,	dragon
50	batik pattern, black and white, sketch,	orchid
60	batik pattern, black and white, sketch,	jasmine flower

C. Using Stable Diffusion to generate images

For the image generation phase, each model is operationalized within a system boasting specific specifications: an Intel Core i9-11900H processor, 16 GB of RAM, NVIDIA RTX 3060 Laptop GPU, 500GB Hard Disk, and the Python programming environment. Across all variants of the Stable Diffusion framework, we use the following hyperparameter to generate images (Table II).

D. Evaluate the model

Following the collection of generated image samples, a comprehensive evaluation is carried out by making use of two crucial metrics: the Inception score and the CLIP score. Inception score measures quality and diversity of generated images based on the model InceptionV3 where given a prompt the image must clearly indicate that such object exists while maintaining the ability to create diverse images [23].

TABLE II
HYPERPARAMETERS TO GENERATE THE IMAGES

Hyperparameters	**Value**
Sampling method	Euler a
Sampling Steps	30
Width, Height	512
CFG Scale	7
Batch size	8

Given the x as the image generated by the generative model and y is the number of classes that exists in InceptionV3 model, inception score calculates the exponent of alignment between the distribution of every image given a prompt and the distribution of the classes itself. Higher number meaning that the images contain clear objects defined in the prompt while maintaining the ability to create diverse images. The equation is described in equation (1).

$$\mathit{Inception\ Score} = \exp\left(\mathbb{E}_x \mathrm{KL}\left(p(x|y) \| p(y)\right)\right) \tag{1}$$

On the other hand, CLIP score calculates the correlation between the prompts and the generated image [21]. Both the prompt and the image are feed through a feature extractor to extract image CLIP embedding v and prompt CLIP embedding c. The CLIP embedding c and v then calculated using cosine similarity among generated images and given prompts with scaling $w = 2.5$. The equation of CLIP score is described in equation (2).

$$\mathit{CLIP\ Score} = w \times \max\left(\cos(c, v), 0\right) \tag{2}$$

E. Stable Diffusion's Training on Bakaran Batik Motifs

To prove the ability of the Stable Diffusion model in the case of real batik motifs, we need local batik motifs data. We chose Bakaran batik because of the poor pattern archiving conditions and the decreasing interest of the younger generation in preserving this batik motif. The following are the steps for testing the stable diffusion model on Bakaran batik motifs:

1) Data Collection

The image data was obtained from the Bakaran Tjokro Batik collection of motifs from Mr. Buchari, who is currently a senior batik maker in Bakaran Village, Pati City, Central Java Province, Indonesia. 52 types of batik motifs can be archived for the dataset as shown in Fig. 1.

(a) (b) (c)

Fig. 1. Raw Data of Batik Bakaran. (a) pattern *"Hujan Mas"*, (b) pattern *"Iwak Etong"*, (c) pattern *"Boket Ayam Alas"*

2) Image Pre-processing

After getting the dataset, it is then processed using vector techniques as image treatment before being augmented and trained. The results of vectoring of raw datasets in Fig. 1 are shown in Fig. 2. We use image augmentation techniques in the form of random rotation and flip for every batik pattern to support the number of datasets during training. The amount of image data after augmentation is 420 images. These images are cropped into 512px × 512px in order to accommodate LoRA training.

(a) (b) (c)

Fig. 2. Processed Dataset. (a) pattern "Hujan Mas", (b) pattern "Iwak Etong", (c) pattern "Boket Ayam Alas"

3) Training the models

Low-rank adaptation of Large Language Models or LoRA is a common technique to fine-tune available pre-trained models especially in Stable Diffusion by modifying the UNet weights based on a new dataset. Each version for Stable Diffusion will be used as the base model for fine-tuning. Every epoch, the model is saved as a checkpoint for further analysis. The fine-tuning with hyperparameters that are shown in Table III.

TABLE III
LORA FINE-TUNING HYPERPARAMETERS.

Hyperparameters	Value
Batch Size	2
Image Repeat	3
Optimizer	AdamW8bit
Learning Rate	0.0001
LR Warmup	10% total steps
Epoch	10

4) Evaluation of the models

To evaluate the model, first we need to generate several patterns of Batik Bakaran. Every version of Stable Diffusion is used together with each LoRA checkpoint that has been trained. To generate images, each version will use the "batik bakaran" as the base prompt combined with the varying prompts described in Table I. Two sampler methods will be used which are Euler ancestral and DPM++ 2M [24]. The image was generated using 20 steps with 7.0 config strength (cfg).

To evaluate the model's ability to generate the Batik Bakaran pattern, VGG-11 is proposed instead of using the CLIP score and inception score [25]. The VGG-11 model will be used as a discriminator between Batik Bakaran pattern and other batik pattern. VGG-11 model was trained on a dataset containing batik patterns with Bakaran styles and non-Bakaran styles as shown in Fig. 3. The VGG-11 model is trained with a default learning rate of 50 epochs. The dataset is augmented with random rotation (around 5 degrees), random horizontal flip, and random crop to increase the number of the samples achieving 520 training samples and 130 validation samples. Within 50 epochs, the VGG-11 model are able to achieve 100% accuracy for both training and validation sets.

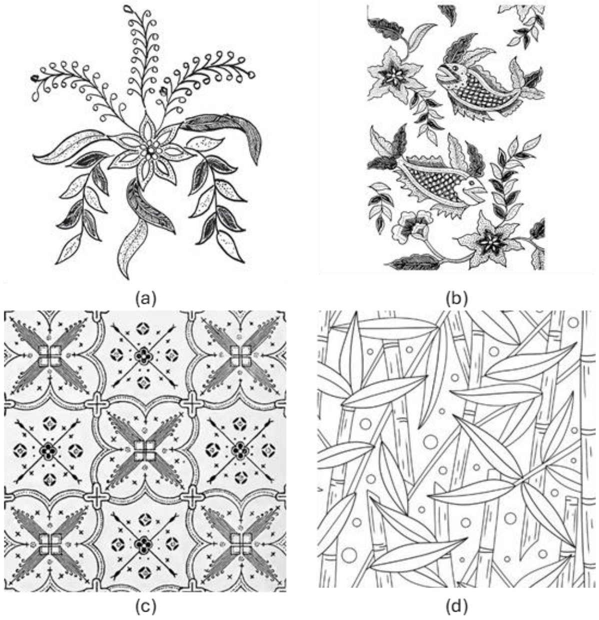

Fig. 3. Dataset for Training VGG-11. (a) and (b) are Batik Bakaran pattern. (c) and (d) are not Batik Bakaran pattern.

The VGG-11 model is trained with the default optimizers with 2 neurons as the output. The last fully connected layer will be used to calculate the probability of an image is either Bakaran styles or non-Bakaran styles. The models are trained with 30 epochs. After training VGG-11, the output will be used to predict the probability of generated images from Stable Diffusion to be Batik Bakaran Pattern by evaluating each saved checkpoint with its prompt strength.

III. Results and Discussion

A. Base Stable Diffusion Model

This investigation makes use of three distinct forms of generative deep learning. The specific names for these are SDXL, Stable Diffusion V1.5, and Stable Diffusion V2.1. Through the use of the inception and CLIP scores, we have completed an evaluation of their creative capabilities. SDXL shines when it comes to inception scores, excelling in the creation of one-of-a-kind images in animal patterns, that is closely followed by V2.1 when it comes to floral designs. On the other hand, when it comes to CLIP scores, V1.5 holds the top spot when it comes to reproducing images that are similar to prompts, closely followed by SDXL, while V2.1 has its own set of advantages (Table IV and Table V). Table IV demonstrates that Stable Diffusion V1.5 has a low variance inception score for all of the different prompts that are displayed. It may be deduced from this that Stable Diffusion V1.5 is capable of producing a variety of prompts that are, for the most part, of the same quality and pattern. Using the CLIP score stable diffusion V1.5, the evaluation reveals that the butterfly and jasmine flower have a higher score than the other two as the variable prompt (Table V). According to the findings, both prompts have higher correlations between the input prompts and the images that were generated due to the prompts.

Fig. 4 illustrates that the butterfly text prompt got the closest results to the visual of SD 1.5 results. Stable Diffusion V1.5 consistent low variance inception scores reveal an ability to maintain image quality and pattern coherence across diverse prompts. This is a pivotal achievement as it suggests that the model can generate visuals with unwavering fidelity to the prompt [26], thereby preserving the cultural essence of the batik motif. Furthermore, the heightened CLIP scores for prompts like "butterfly" and "jasmine flower" (Table V) underscore the model's proficiency in aligning with specific batik motifs. This alignment is vital for infusing a sense of authenticity and coherence into the generated images, aligning them seamlessly with the traditional artistic standards [27].

TABLE IV
COMPARISON OF INCEPTION SCORE

Varying Prompt	V1.5	V2.1	SDXL
KOMODO	2.126	2.120	1.971
BUTTERFLY	2.383	1.896	2.458
DRAGON	2.176	2.372	3.394
ORCHID	2.231	3.120	2.677
JASMINE FLOWER	1.847	2.540	2.301

TABLE V
COMPARISON OF CLIP SCORE

Varying Prompt	V1.5	V2.1	SDXL
KOMODO	30.366	27.150	29.224
BUTTERFLY	33.203	29.300	32.685
DRAGON	31.568	28.331	30.036
ORCHID	31.288	29.349	32.175
JASMINE FLOWER	33.957	32.617	32.575

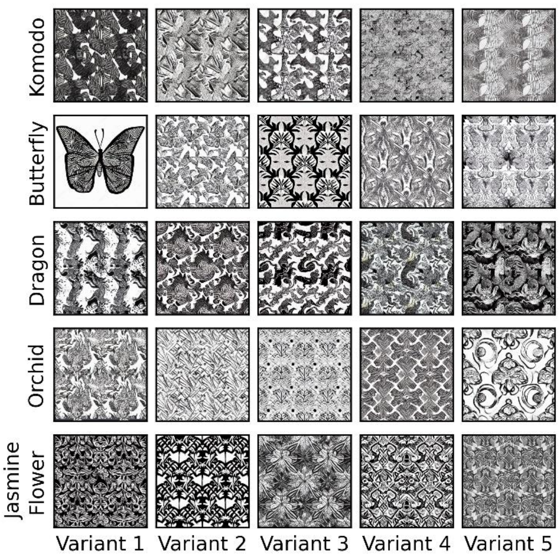

Fig. 4. Stable Diffusion v1.5 Results

According to Table IV, the inception score appears to have the highest score for the orchid when it is used as the variable prompt in the Stable Diffusion V2.1 algorithm. The findings suggest that the generative model may have produced a number of different kinds of orchids, as indicated by the results. On the other hand, the CLIP score has a relatively low variety (Table V). The fact that this is the case indicates that the V2.1 possesses comparable skills in terms of generating images in accordance with the prompts for the batik pattern across a variety of prompts.

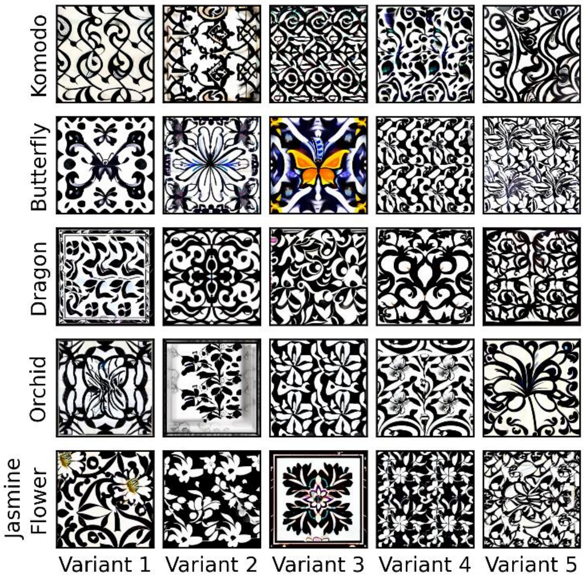

Fig. 5. Stable Diffusion v2.1 Results

Fig. 5 illustrates that the orchid text prompt got the closest results compared to other animal or flora text prompts in SD 2.1 batik pattern. The performance of Stable Diffusion Version 2.1, with its peak inception score observed for "orchid" prompts, hints at its potential to explore and diversify orchid-related batik motifs. However, the model's consistently low CLIP score variance signifies its ability to uphold image quality across various prompts [28]. This reliability makes it appealing for artists seeking to balance traditional and innovative design elements.

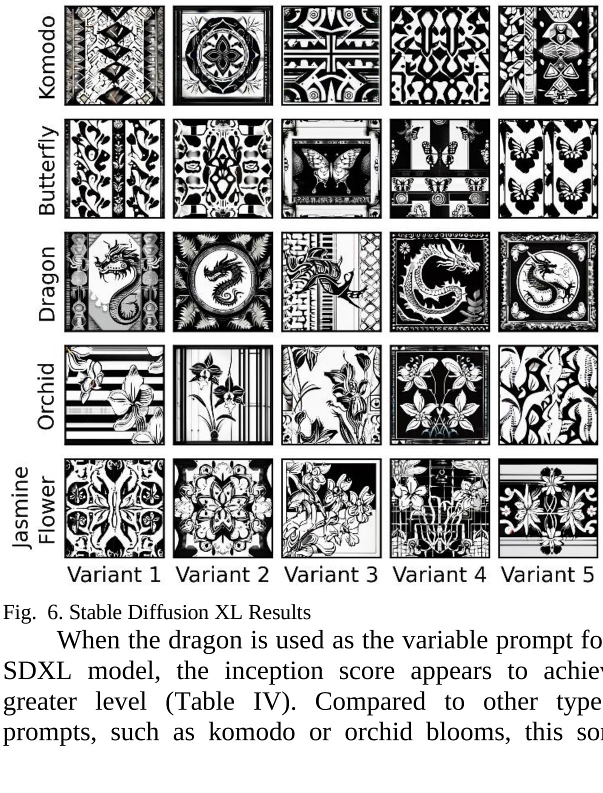

Fig. 6. Stable Diffusion XL Results

When the dragon is used as the variable prompt for the SDXL model, the inception score appears to achieve a greater level (Table IV). Compared to other types of prompts, such as komodo or orchid blooms, this sort of depression is the one that has the potential to yield a wide variety of Dragons. In contrast, the CLIP score reveals a different narrative (Table V), which may be found here. It would appear that the varying prompt for the butterfly, orchid, and jasmine flower has a greater score than the Komodo or dragon prompt.

SDXL's intriguing results deserve careful consideration. The SDXL model's advantages in diverse image generation tasks, medical imaging, image reconstruction, and multimodal image translation underscore its potential in addressing various challenges across different domains. The results of high inception scores with "dragon" prompts (Fig. 6) suggest its proficiency in generating a wide spectrum of dragon-related batik motifs, catering to a significant facet of traditional artistry. However, the CLIP score presents an alternate narrative, with "butterfly," "orchid," and "jasmine flower" prompts garnering higher scores. This discrepancy highlights the multifaceted nature of SDXL, demonstrating its ability to serve diverse creative needs but emphasizing the importance of a nuanced metric selection when leveraging its capabilities [29]. Furthermore, SDXL generates diverse and realistic images across a wide range of tasks without the need for paired training data, demonstrating its capability in unsupervised image-to-image translation [30]. The SDXL showed good results due to the model's capacity to efficiently parametrize bilinear interactions between visual and textual representations demonstrating its potential in learning high-level associations between question meaning and visual concepts in image captioning tasks [31].

According to the findings presented in Table IV and Table V. In comparison to V1.5 and V2.1, the SDXL demonstrated the highest inception score as a result. Additionally, SDXL demonstrated encouraging results in the spectrum of alternative images on animals, with V2.1 demonstrating the best performance in the generation of floral batik motif alternatives. In contrast, the CLIP score indicated that V1.5 performed well in terms of alignment between the prompts and the images that were generated. This was in contrast to the performance of V2.1 and SDXL in terms of generating photos that were either floral or animal.

The results from our evaluation of Stable Diffusion models provide invaluable insights into their performance in generating images with varying batik motif prompts, aligning with our research endeavor to enhance traditional artistry through a generative deep learning approach. Stable Diffusion Version 1.5, as evident in Fig. 4, displays a low variance in inception scores across diverse prompts. This exceptional consistency suggests that the model can generate images of similar quality and pattern regardless of the input prompt [18, 20]. This attribute could significantly streamline batik designers' creative process, ensuring artistic integrity and coherence across a spectrum of motifs [11].

The results of this study found at least three results. First, the use of Stable Diffusion V1.5 is highly recommended in batik patterns with certain principles or characters that require specific prompts related to the design characteristics of the motif. Second, SDXL is recommended in the visual variation of batik design motifs. This can be useful for the batik industry for processing alternative designs by ordering certain designs that appear quickly (Fig. 6). Third, V2.1 is recommended in generative batik with floral motifs (Fig. 5).

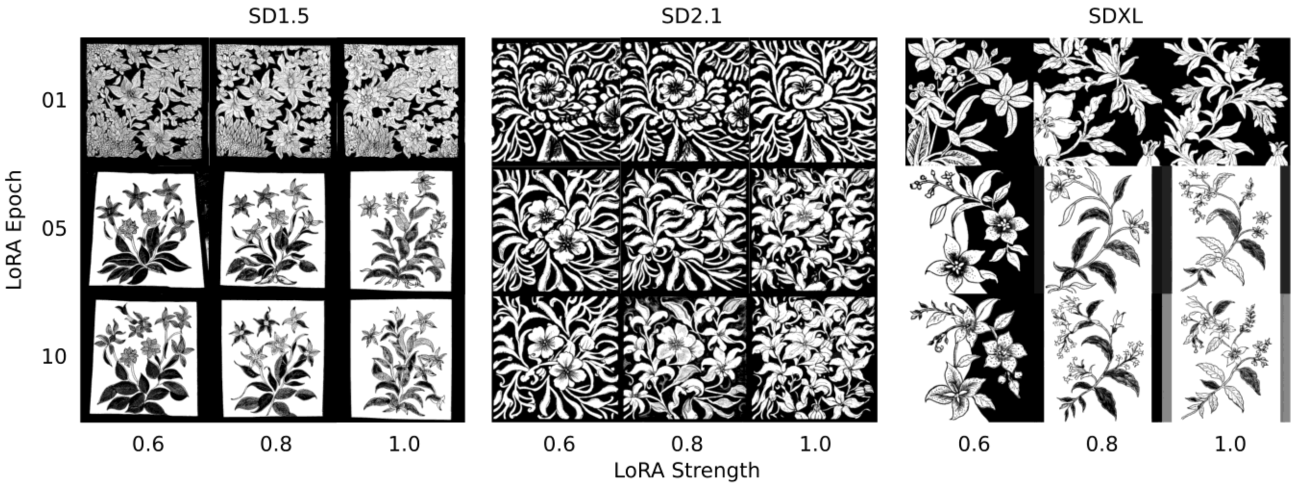

Fig. 7. Batik Bakaran Generated Pattern using jasmine flower as a prompt with DPM++ 2M sampler and Karras Scheduler. (a) Stable Diffusion v1.5, (b) Stable Diffusion v.2.1, and (c) Stable Diffusion XL.

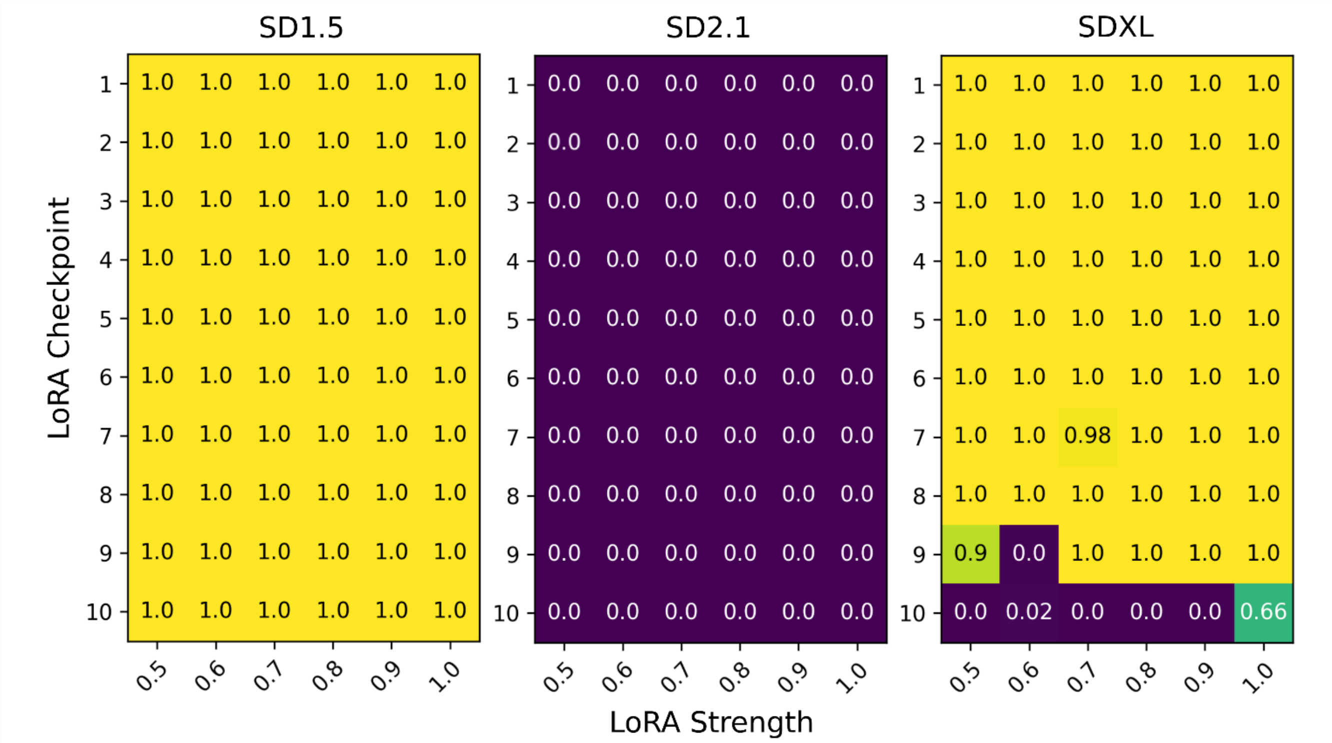

Fig. 8. Batik Bakaran LoRA Evaluation with VGG-11 for jasmine flower as a prompt with DPM++ 2M sampler and Karras Scheduler. (a) Stable Diffusion v1.5, (b) Stable DIffusion v.2.1, and (c) Stable Diffusion XL.

B. Stable Diffusion Fine-Tuning for Batik Bakaran Pattern

In order to investigate further the ability of the generative model, especially Stable Diffusion, we conduct research on its ability to generate a specific style of batik coming from Bakaran Village, Pati Regency, Central Java Region, Indonesia. All three models were trained using the same datasets and hyperparameters. The LoRA was trained with 10 epochs with 6 different LoRA strength. The samples for epoch 1, 5, and 10 and LoRA strength of 0.6, 0.8, and 1.0 for all Stable Diffusion versions are shown in Fig. 7.

For each varying prompt, we evaluate by using VGG-11 to predict the probability (likelihood) for a pattern to be Batik Bakaran pattern. As a result of the “Jasmine Flower” prompt, most of the generated images from SDXL are considered as Batik Bakaran patterns, On the other hand, the results of Stable Diffusion V2.1 are not considered as Batik Bakaran patterns at all. Stable Diffusion V1.5 stands between Stable Diffusion XL and Stable Diffusion V2.1. The evaluation results for “Jasmine Flower” prompt can be seen in Fig. 8.

When comparing all images generated by three Stable Diffusion versions, varying prompt, LoRA checkpoints, and LoRA strength, SDXL achieves the highest probability of producing Batik Bakaran pattern followed by Stable Diffusion V1.5, and lastly V2.1 as shown in Fig. 9. This result is aligned with the Stable Diffusion experiments above.

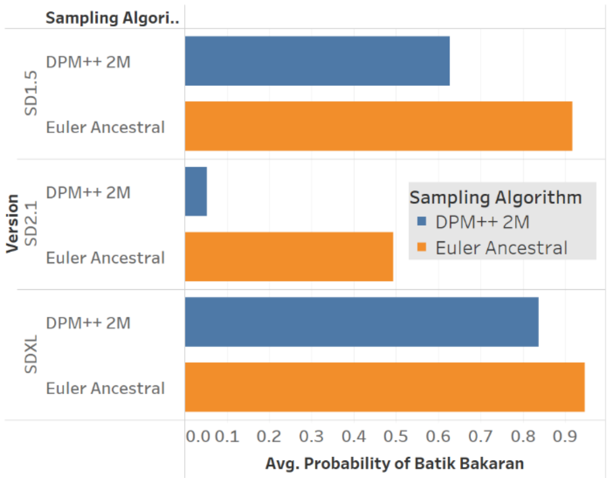

Fig. 9. Generated Images Probability of Different Stable Diffusion Versions

Our study provides a profound understanding of how Stable Diffusion models can enhance traditional artistry in batik motif design. The models exhibit distinct strengths and performance nuances, offering artists and designers valuable tools for preserving cultural heritage while fostering innovation in their creative endeavors. These insights hold significant implications for converging deep learning and traditional art, enabling a harmonious fusion of technology and cultural richness.

IV. Limitation

This study used two different measures, inception, and CLIP scores, to judge how the models performed. Inception scores help us see how creative the models can be, while CLIP scores show how well they match specific prompts. The challenge is the model that's suitable for being creative might not always align perfectly with the prompts, and vice versa [22]. For measuring performance in a specific case, this study used VGG-11 which is smallest variant of VGG in regard to number of parameters. For future research, various evaluation metrics, such as Frechet Inception Distance [32], Perceptual Path Length [33], and more advanced method of evaluations for evaluating styles are needed to show the unrevealed aspects of the generative model.

V. Conclusion

Based on observations using the inception scores, SDXL has more potential to produce more distinct images given multiple prompts, followed by V2.0 and V1.5. On the other hand, by observing the CLIP score, V1.5 has more potential to produce images that are more similar to the prompt, followed by SDXL and V2.0. Based on these results, we can suggest that V1.5 and SDXL are the two best models with tradeoffs. Looking at the resulting images, it is evident that these models can significantly improve the creative process in batik motif design. The Stable Diffusion V1.5 excels in preserving traditional batik patterns and ensuring seamless alignment with specific instructions, making it an excellent choice for artists who want to maintain cultural authenticity. On the other hand, SDXL produces highly distinct and innovative images, ideal for artists who want to push the boundaries of tradition while quickly creating alternative motif designs. When faced with a local batik pattern, SDXL also performs better according to its evaluation using VGG-11 followed by V1.5. On the other hand, V2.0 does not lead in any metrics that are used in this research, its consistent lack of performance in inception scores, CLIP scores, and VGG-11 evaluation makes it an unreliable choice. These findings underscore the important role of generative deep learning in the future of traditional arts, where technology and tradition converge to drive innovation and preservation.

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