Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Enhancing Supervised Learning through Empirical Enrichment Using Style Transfer Generative Datasets

Djarot Hindarto[1)*]
[1)]Prodi Informatika, Fakultas Teknologi Komunikasi dan Informatika, Universitas Nasional, Jakarta, Indonesia
[1)]Djarot.hindarto@civitas.unas.ac.id

Submitted :Dec 12, 2023 | **Accepted** : Jan 3, 2024 | **Published** : Jan 5, 2024

Abstract: An innovative strategy for improving supervised learning by utilizing empirically enriched datasets through the application of generative style transfer techniques. Within the realm of artificial intelligence, supervised learning has emerged as a significant domain. However, the challenge of acquiring datasets that are both representative and diverse persists. To tackle this issue, this research integrates the notion of style transfer to broaden the range of data accessible for supervised learning models. This method employs the style transfer process to generate diverse style variations within the existing data. Incorporating various image variations enhances the dataset and enables the model to gain a deeper comprehension of the image's content. Experiments were performed utilizing a conventional dataset that was enhanced using a style transfer technique and subsequently inputted into a supervised learning model. The results demonstrate substantial enhancements in model performance, particularly in terms of its ability to generalize to new test data. This confirms the efficacy of this approach in enhancing the quality of supervised learning. These findings emphasize the significant potential of employing style transfer in dataset enrichment to improve and intensify model comprehension in managed learning scenarios, as well as its implications in the advancement of artificial intelligence technologies that are more flexible and capable of adjusting to various visual scenarios.

Keywords: Artificial Intelligence; Dataset Enrichment; Generative Style Transfer; Supervised Learning Model; Various Visual Dataset

INTRODUCTION

In recent years, there has been significant advancement in the field of artificial intelligence (Schramm et al., 2023), (Taha et al., 2023), particularly in the area of supervised learning. Nevertheless, despite the current progress, technological advancements are frequently impeded by the caliber of the datasets employed for model training. The datasets that are currently accessible often fail to accurately represent the wide range of diversity and intricacy found in the real world. This limitation needs to improve the capacity of models to comprehend the existing variations. In the domain of supervised learning (Hindarto & Santoso, 2023), where models are trained to discern patterns and apply their comprehension to unfamiliar data, the necessity for extensive and diverse datasets is crucial. Within this specific context, the objective of this research is to rectify the deficiencies in the dataset by introducing a novel methodology that integrates generative style transfer techniques. This approach aims to enhance the dataset utilized in supervised learning by generating stylistic variations within the current data. By using the principle of style transfer, one can apply diverse and innovative visual styles to preexisting datasets. This enables models to effectively identify and comprehend intricate variations in style within the data while preserving the fundamental essence of the original content. This approach is expected to address limitations in dataset representation, enhance the model's capacity to generalize information to unfamiliar data, and create new possibilities for improving model comprehension within the framework of supervised learning (Fan et al., 2024), (Hindarto & Santoso, 2022), (Hindarto & Handri Santoso, 2021), (Hindarto, 2022).

In datasets, the inadequate representation of a vast array of real-world visual content poses a significant obstacle to the advancement of supervised learning. When trained on datasets that are overly specific or limited, models may need help to identify patterns in previously unseen data. Consequently, when applied to practical scenarios, a model's capacity to accurately capture and comprehend critical visual style variations may be impeded by its dependence on less representative datasets. This challenge pertains to the propensity of models to exhibit reduced

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

responsiveness towards discrepancies in aesthetics or distinct visual attributes present in real-world data. The inability of the model to interpret intricate visual style variations, including disparities in composition, texture, or other aesthetic components, can be attributed to the utilization of restricted datasets.

Consequently, while the model might acquire knowledge of particular patterns within the training dataset, its capacity to extrapolate to novel circumstances or data that it has not encountered before is constrained. In the realm of artificial intelligence, where successful applications necessitate models capable of adjusting to the visual diversity that is inherent in the environment, this type of issue assumes critical importance. Consequently, addressing the constraints of the dataset and incorporating visual style variations constitute the primary emphasis of this study. There is an expectation that by surmounting constraints in the training dataset, the model's capability to identify and comprehend an assortment of intricate and opulent visual styles will be enhanced. Such progress would subsequently facilitate the creation of artificial intelligence applications (Yuan et al., 2023), (Meng et al., 2023) that exhibit greater adaptability and responsiveness to diverse visual contexts encountered in the real world.

At present, a multitude of methodologies have been devised to augment the diversity of datasets. These include data augmentation through straightforward transformations and the implementation of transfer learning techniques to assimilate insights from alternative datasets. Techniques such as data augmentation via simple transformations and transfer learning have been implemented to increase the variety of datasets. Despite its utility, this approach could be more capable of generating substantial stylistic variations, particularly in the case of visual data exhibiting a range of stylistic complexities. Frequently, these techniques need to create adequate stylistic diversity, mainly when applied to images that encompass an abundance of intricate and diverse visual styles.

In order to enhance supervised learning, this study proposes a novel method that combines generative style transfer techniques to generate style variations on existing datasets. The implementation of style transfer enables the incorporation of diverse and inventive aesthetics into pre-existing data, thereby enhancing the depiction of variations within a dataset while preserving the fundamental content of the original data.

With the aim of comprehending and enhancing the caliber of supervised learning, the initial research inquiry examines the visual enhancement capabilities of datasets through the implementation of generative transfer styles. In contrast, the subsequent investigations look at the degree to which the suggested methodology enhances the model's capacity to extrapolate to novel data. Two research questions are as follows: In what ways can the application of generative style transfer enhance the quality of supervised learning in visual contexts by enriching datasets? To what degree does the proposed methodology enhance the model's capacity to extrapolate to data that it has never encountered before?

The primary objective of this study is to devise and implement a novel methodology that efficiently enhances the dataset utilized in supervised learning through the implementation of generative style transfer techniques. The primary objective is to enrich datasets with greater diversity and visual representation, thereby enabling models to acquire a more profound comprehension of stylistic fluctuations in authentic graphic material. Furthermore, an exhaustive evaluation of the effect that utilizing this enriched dataset has on the performance of supervised learning models is another objective of this research. The assessment encompasses the model's capability to identify, decipher, and handle an assortment of intricate visual styles. The utilization of an enriched dataset is anticipated to enhance the model's capacity to handle the complexities of force variations in visual data and generate more accurate and general representations of novel, unobserved scenarios. This research potentially yields a substantial impact on the advancement of generative style transfer methodologies utilized in the domain of supervised learning to augment datasets. This contributes to a more comprehensive understanding of the ways in which supervised learning can be used to enhance the quality of datasets, optimize the performance of models, and further develop our knowledge of its applications in artificial intelligence.

LITERATURE REVIEW

The literature review regarding the application of style transfer for enriching datasets within the domain of deep learning provides a comprehensive examination of the progression of this method in generating innovative iterations for datasets, enhancing comprehension of its influence on the caliber of supervised learning, and investigating diverse approaches utilized to improve model performance via visually enriched datasets. Style Transfer is a concept employed in the domains of fine arts, natural language processing, and fixed trajectories. It is utilized to manage policies within a Deep Reinforcement Learning framework. The Neural Policy Style Transfer (NPST)1 algorithm is capable of transferring style while preserving content. Experiments are conducted in catch-ball games and real-life situations (Fernandez-fernandez et al., 2022). Utilizing Neural Style Transferring algorithms, the study proposes a method for generating fully aligned synthetic multispectral images from authentic misaligned unmanned aerial vehicle images. For every initial misaligned image, the process generates new synthetic aligned images, which concludes with channels that are perfectly aligned. Experimental results indicate that the newly developed channels bear a resemblance to the original ones, while two case studies illustrate the practicality of the methodology (Vieira et al., 2023). This paper employs CNN to generate a steganographic image containing the semantic content of a cover image that conceals a secret image. Destylization and concealed layered

*name of corresponding author

style characteristics are implemented via conditional generative adversarial networks in this method. The algorithm is assessed in terms of quality loss and visual similarity. The ImageNet dataset achieves a PSNR of 43.95 dB, an SSIM of 0.95, and a VIF of 0.93, rendering it more resistant to Steg Expose than conventional techniques (R, 2022). Based on the ESPCN model, this paper proposes a ceramic decoration pattern style migration algorithm. The algorithm sharpens the image using the Laplace operator, generates low-resolution images via down sampling, and reconstructs the low-resolution image using ESPCN super-resolution reconstruction. This approach optimizes the rendered images by decreasing the number of iterations, enhancing the edge distribution, and improving image quality and definition. The primary objective of this novel methodology is to optimize the operation of multi-robot systems (Huang et al., 2021). This article examines the evolution of style transfer algorithms with a particular emphasis on the utilization of Generative Adversarial Networks (GANs) in domains such as literature, industry, and medicine. It examines the methodology, assesses the algorithms' efficacy, and deliberates on prospective avenues of research as well as obstacles pertaining to GAN-based style transfer algorithms (Cai et al., 2023). Neural style transfer technology improves efficiency and generation effect, but semantic description networks complicate and unnaturally connect regions. Improved regional multi-style transfer using attention mechanism and instance segmentation is proposed. A convolutional block attention module and conditional instance normalization layer enable multi-style transfer while preserving semantic information. This method improves original content and visual effects with diverse styles, according to experiments (Ye et al., 2023). This paper proposes an optimal transport-based assignment to solve arbitrary Neural Style Transfer (NST) in content images. The assignment allows multiple sub-style components per content feature by distributing stylized and styled images similarly—weighted style transfer blends sub-style-stylized results. Numerous experiments show that the proposed method yields promising stylized results (Li et al., 2023). Chinese character style transfer is complicated. Current methods ignore Chinese sentences and multiple characters and focus on single-character images. A new Chinese poetry style transfer method uses Smooth L1 loss and a novel key-attention mechanism generative adversarial network (KAGAN) to generate high-quality images. The technique improves the SSIM evaluation metric by nearly 2% over other transfer methods (Yang et al., 2022).

Although the use of style transfer in various domains of artificial intelligence has been documented in the past, there are significant gaps in the literature. Application to visual datasets is emphasized, with no additional investigation into the potential of this domain. A significant research gap exists regarding the connection between style transfer and artificial intelligence domains like natural language processing and reinforcement learning. Furthermore, the existing literature needs to sufficiently address the point where comprehensive evaluation and standardized benchmarking pertaining to the efficacy, stability, and scalability of style transfer methods are concerned. Additional research is warranted to examine the ethical implications, generalizability, and interpretability of style transfer in diverse social contexts and domains.

METHOD

The proposed method aims to improve the visual quality of supervised learning datasets by incorporating generative style transfer. This approach seeks to enhance model capabilities by introducing force variations to the dataset, enabling the model to adapt better to previously unseen data. Therefore, this approach not only enhances the depiction of the dataset but also establishes a robust basis for the model to recognize and categorize data with varied and unforeseen stylistic attributes.

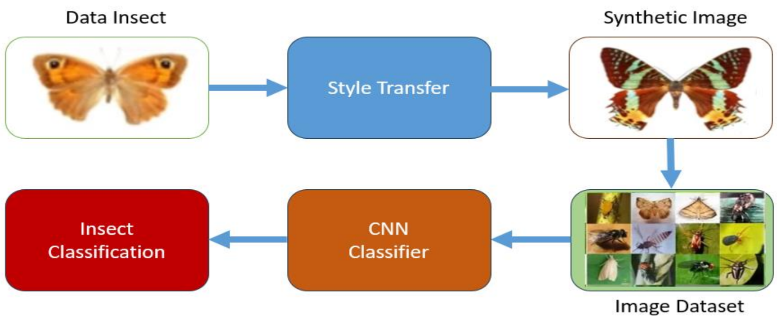

Figure 1. Proposed Methodology
Source: Researcher Property

Figure 1 illustrates the proposed methodology, which commences with an initial step utilizing an insect image dataset as the basis for research. The subsequent step entails style transfer, a method employed to transfer the aesthetics or style from a different dataset into the insect image dataset being utilized. The objective of this process is to enhance the insect dataset by incorporating diverse visual styles derived from other datasets. The subsequent phase in this methodology involves generating synthetic images as a consequence of the style transfer procedure.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

These artificial images are supplements to the initial dataset of insect images. The purpose of integrating these synthetic images is to enhance the diversity and representation in the dataset, thereby introducing a more comprehensive range of visual styles in insect datasets that may have previously lacked variation in style. The dataset, which has been augmented with synthetic images, is subsequently employed in the training phase of a Convolutional Neural Network (CNN) classifier. The CNN is trained using a diverse dataset, which is anticipated to enhance the classifier's capacity to identify and categorize insect images accurately. This approach employs style transfer techniques as a means to improve diversity in the dataset, enabling the classifier to observe a broad range of visual styles within the context of insects. By utilizing a dataset that has been enhanced, it is anticipated that the classifier will acquire knowledge from a diverse array of visual differences and consequently achieve superior classification accuracy, even when presented with previously unseen insect images. This will enhance the model's capacity to comprehend the intricate variations of insect images in real-world scenarios.

Table 1. Pseudo-code Style Transfer
Source: Researcher Property

Pseudo-code for style transfer
While epoch < and equal maximal epoch:
Draw sample image from domain k
Draw sample from domain l
Generated image A(k) and B(l), reconstructed image A(B(k)) and A(B(l))
Compute discriminator loss
Update discriminator C(k)
Compute discriminator loss
Update discriminator C(l)
Compute generator loss
Update generators A and B
epoch += 1

Table 1, the pseudo-code employed for style transfer outlines the primary procedures involved in generating a novel image that amalgamates styles from two distinct domains, K and L. During each epoch iteration, images are sampled from both domains. Subsequently, the generator is utilized to produce novel images denoted as A(k) and B(l), alongside reconstructed images designated as A(B(k)) and A(B(l)), which serve as representations of forces originating from distinct domains. Subsequently, a computation is executed to assess the disparity between the original and generated images, specifically in relation to the discriminator loss. The process is performed sequentially for both domains, with the discriminator being updated for each domain once the computation of the discriminator loss is finished. The last stage entails the calculation of generator loss, wherein generators A and B are modified to enhance image quality. This iteration continues until the number of epochs reaches a pre-established threshold. This process utilizes the principles of style transfer to enable the model to incorporate influences from two distinct domains, K and L, and subsequently update the generator and discriminator in an alternating manner. This allows the model to acquire the ability to produce novel images in the intended style while considering the variations in style between the two distinct domains. The update process is iteratively executed throughout the epoch, leading to incremental enhancements in the model's capacity to facilitate force transfer across diverse domains.

The illustration presented in Figure 2 illustrates the style transfer application of a Generative Adversarial Network (GAN). Generative Adversarial Networks (GANs) is a deep learning approach comprising a generator and discriminator, which are neural network models that collaborate to generate novel and lifelike images. GANs are utilized to transfer visual styles from one image to another in the context of style transfer, resulting in intriguing and inventive style variations. The style transfer procedure using GANs commences with the utilization of authentic images depicting a variety of fauna, including chickens, cows, ducks, and lions. Subsequently, the generator within the GAN generates new images that emulate the aesthetic of reference images, such as artwork or a particular visual style, via iterative processes. This procedure is carried out through the utilization of representations that the generator has acquired from the initial animal dataset, as well as styles from the reference dataset. The outcome of this procedure is visually altered images of animals that reflect the transferred aesthetic. Illustrations depicting cattle, poultry, ducks, and lions, for instance, might incorporate the visual attributes or aesthetic qualities of renowned paintings, distinct artistic movements, or one-of-a-kind optical configurations. This procedure enables the generation of innovative new images through the amalgamation of components from the source image of the creature and the transferred aesthetic. In supervised learning, the implementation of style transfer via GANs has numerous applications. It is utilized not only in the realm of visual aesthetics but also to enrich model learning datasets. By acquiring knowledge and identifying variations in aesthetics from diverse

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

origins, this procedure enables the model to generate more comprehensive depictions and exhibit an enhanced capacity for extrapolating across a range of visual aesthetics.

Nevertheless, keep in mind that the application of GANs to style transfer presents a number of obstacles. Control over the final product is one of them, as this process may generate undesirable or inconsistent output. Additionally, the assessment and quantification of the transferred style's quality are matters of concern, as subjective evaluation frequently enters into the process of determining the resulting style transfer's originality and suitability. In general, the utilization of GANs in style transfer is illustrated in Figure 2. This application holds significant promise for augmenting datasets for supervised learning across diverse domains and generating an array of novel visual styles.

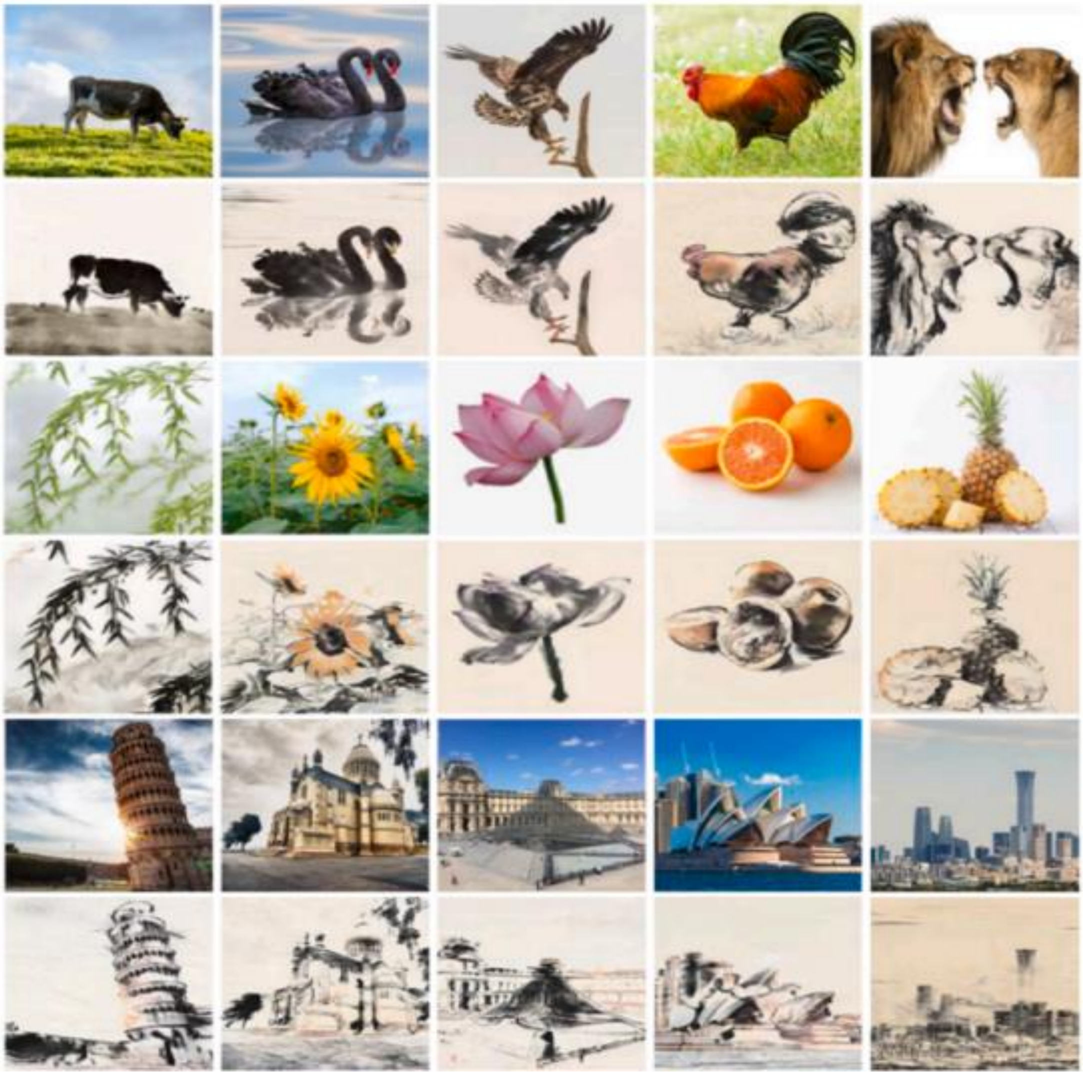

Figure 2. Style transfer Generative Adversarial Network (Wang et al., 2023)

Figure 2, GAN style transfer involves two competing neural networks: a generator and a discriminator. One image's style and another's content are used to generate new images. The discriminator compares the generator-produced image to the original. The generator competes to deceive the discriminator while the discriminator improves image recognition in GAN training. The generator produces more stylistically authentic images as the discriminator's capability to differentiate between the generated and original images continues to enhance. Over time, the generator can generate new images in the same style as the source image, making it harder for the discriminator to tell them apart. This GAN approach has improved style transfer, allowing the creation of compelling and authentic images.

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

RESULT

The following is an experiment for Style Transfer image:

```
#Pre Train VGG19
# Move the model to GPU, if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
vgg.to(device)
```

```
Output
```

```
Sequential(
  (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1)
)
  (1): ReLU(inplace=True)
  (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1
))
  (3): ReLU(inplace=True)
  (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_
mode=False)
  (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
  (6): ReLU(inplace=True)
  (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1,
1))
  (8): ReLU(inplace=True)
  (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_
mode=False)
  (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (11): ReLU(inplace=True)
  (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (13): ReLU(inplace=True)
  (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (15): ReLU(inplace=True)
  (16): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (17): ReLU(inplace=True)
  (18): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil
_mode=False)
  (19): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (20): ReLU(inplace=True)
  (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (22): ReLU(inplace=True)
  (23): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (24): ReLU(inplace=True)
  (25): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (26): ReLU(inplace=True)
  (27): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil
_mode=False)
  (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
```

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

```
  (29): ReLU(inplace=True)
  (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (31): ReLU(inplace=True)
  (32): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (33): ReLU(inplace=True)
  (34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1
, 1))
  (35): ReLU(inplace=True)
  (36): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil
_mode=False)
)
```

Figure 3. Pre-Train VGG19
Source: Github.com

Figure 3, The convolutional neural network VGG19 has 19 layers. This structure extracts image features using iterative convolutions and a max-pooling layer. The convolution layer uses a 3x3 filter with stride one and padding 1 to maintain image dimensions. The model is non-linearized with ReLU activation after each convolution. The first convolutional layer extracts 64 features from an image. Before deconvolution on the next layer, ReLU activates the results. This process repeats twice before max-pooling, halving the image size. Repeat several times, adding features to each layer. Later layers extract more complex features like edges, patterns, and textures. After convolution layers, several fully connected layers combine removed features into an abstract feature vector. VGG19 is designed for image classification, but its structure is helpful for transfer learning. This model can extract features for object detection, segmentation, and image tagging by removing the fully connected layers at the end. Its proven capabilities and simple structure make it a popular image-processing tool.

Figure 4. Process Style Transfer
Source: Researcher Property

Figure 4, Transferring styles between images is called style transfer. When a butterfly image is the content image and a landscape painting is the style image, the style transfer algorithm will apply the landscape painting's aesthetics to the butterfly image. First, load the two images into the algorithm. The butterfly image will retain its shape and structure, while the landscape painting will import its patterns, colors, and textures into the content image. This process uses deep learning models like CNNs, VGG19, or other pre-trained models. This model has layers trained to identify structural and stylistic image features. Next, the style transfer algorithm optimizes the content image (butterfly) to match the style image's landscape painting styling. To reduce content-style differences, this process iteratively adjusts content image pixel values. Style transfer creates a butterfly image with landscape painting-inspired aesthetics, patterns, and colors. The image is a unique blend of the butterfly image's structure and the landscape painting's visuals. This process produces aesthetic results and shows the model's ability to

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

transfer visual aesthetics between images, which has broad implications for digital art, design, and image processing.

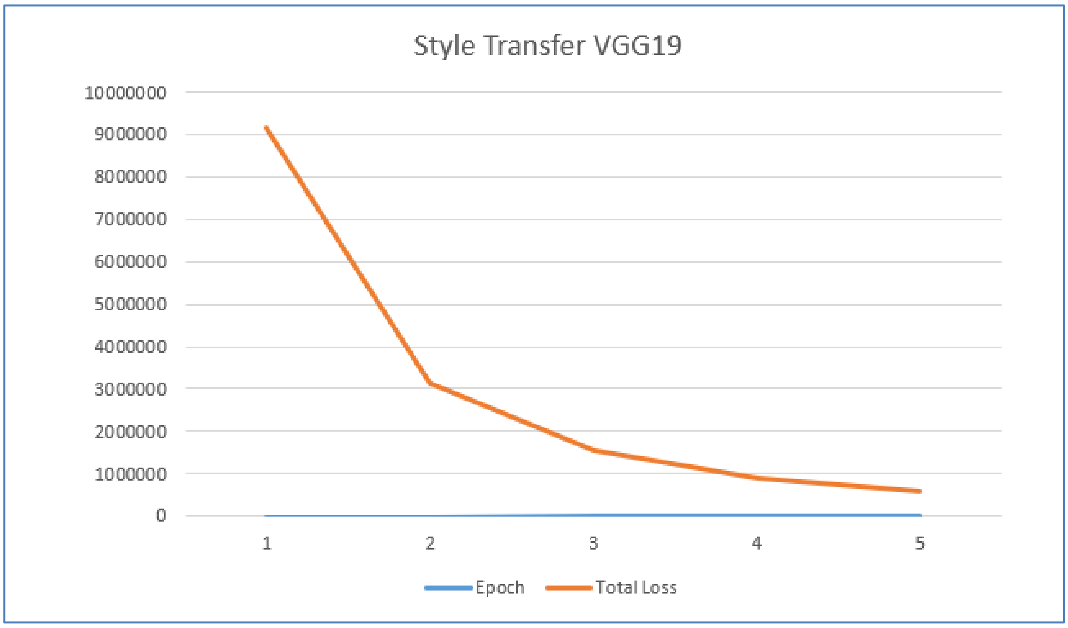

Figure 5. Process Style Transfer
Source: Researcher Property

Minimum loss is achieved through optimization iterations in style transfer. This total loss includes content and style loss from the initial content image to the style transfer. Content loss measures the visual content difference between the style transfer image and the initial content image. Style loss measures how much the style transfer image has adapted to the source image's artistic style. The total loss at each iteration shows how style transfer has improved. The algorithm improves content-image style matching with each iteration, lowering the total loss value. Each optimization step reduces content and style differences between the transferred style image and the source image, improving harmony. The total loss value decreases significantly from iteration to iteration, indicating progress toward the desired image. The style transfer algorithm is improving at matching the source image's content and visual style, as shown by the decrease in total loss. The style transfer results show success when the total loss value changes from iteration to iteration to match the content image and desired style.

Figure 6. Result Style Transfer
Source: Researcher Property

Figure 6, With a butterfly image as the content image and a landscape painting as the style image, the butterfly image has a striking visual style transformation. Landscape painting aesthetics were transferred to the butterfly image, dramatically changing its appearance. The style transfer image shows butterflies with landscape painting-inspired colors, patterns, and textures. The butterfly image reflects the landscape painting's bright colors, natural nuances, and visual composition. Landscape painting styles like brush strokes, texture, and color composition blend well with the butterfly's wings and body. This transformation combines butterfly nature with landscape painting aesthetics to create a unique and exciting image. The style transfer results show the algorithm's ability to transfer and combine visual styles from source images to create excellent aesthetic work. The style transfer algorithm can change texture, pattern, and visual structure between two very different images, not just color. This shows the potential of style transfer techniques in image processing, digital art, and design to create unique and exciting works that combine aesthetics from different sources.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 9, Number 1, January 2024
DOI : https://doi.org/10.33395/sinkron.v9i1.13229
e-ISSN : 2541-2019
p-ISSN : 2541-044X

DISCUSSIONS

In what ways can the application of generative style transfer enhance the quality of supervised learning in visual contexts by enriching datasets?

The utilization of generative style transfer holds significant promise in enhancing the caliber of supervised learning within a visual framework by augmenting the dataset employed. Generative style transfer enables the application of a particular style or aesthetic from one dataset to another dataset, thereby enhancing the visual variety within the dataset used for learning. Generative style transfer applications can enhance datasets by augmenting the range and heterogeneity of visual styles. In supervised learning, the presence of a diverse range of examples in the training data is crucial for the model to acquire and apply information effectively. Through the utilization of style transfer, it is possible to enhance a dataset by incorporating stylistic variations that were not initially present in the original dataset. These variations can encompass disparities in texture, composition, or other visual attributes. For instance, a model that has been trained to identify images of animals could gain advantages from a dataset that has been enhanced with various artistic styles or types of art. This would broaden the model's comprehension of the diverse visual representations of the same object. In addition, the utilization of style transfer can also enhance the dataset's quality by mitigating any bias or inequality that may be present in the original dataset. Style transfer can improve the balance and representativeness of datasets by incorporating styles or aesthetics from diverse data sources, particularly those with more balanced representation. This process facilitates the creation of datasets that better capture the variations in visual data.

Moreover, style transfer can enhance the interpretability of models. By augmenting datasets with diverse visual styles, models can become more adaptable in comprehending and interpreting variations in style from various data sources. This can facilitate the advancement of models that are highly adaptable and capable of effectively handling a broader spectrum of visual scenarios. In general, the use of the generative transfer style greatly enhances the dataset for supervised learning. By expanding the range of styles, improving the quality of the dataset, and enhancing the interpretability of the model, style transfer becomes a precious tool for improving the effectiveness of supervised learning in visual domains.

To what degree does the proposed methodology enhance the model's capacity to extrapolate to data that it has never encountered before?

The proposed methodology exhibits significant potential to enhance the capacity of models to extrapolate novel data that has yet to be encountered previously. An important benefit of this methodology is the incorporation of style transfer, which enhances the dataset by adding diverse visual styles from various data sources. By integrating artificially generated images using the style transfer technique into the training dataset, the model is capable of learning from an expanded variety of visual styles. This enables the model to encounter and assimilate a diverse range of styles or perspectives that it may not have previously experienced. By increasing the range of visual styles in the dataset, the model becomes more flexible in adapting to previously unseen variations. Models trained using this enhanced dataset exhibit an increased likelihood of accurately identifying and extrapolating information from novel data that was not included in the training dataset. For instance, if a model is trained to identify insects in images with diverse styles from various sources, it will likely have an improved capability to categorize pictures of insects that possess a style or appearance that is absent in the training dataset.

Furthermore, the utilization of synthetic images for style transfer can aid the model in discerning the fundamental patterns or characteristics of visual style variations. Through comprehensive analysis and examination of stylistic variations from various sources, models acquire enhanced proficiency in determining the essential attributes that distinguish different visual styles. This grants the model the capacity to extract crucial information from unfamiliar data. Although this approach enhances a model's ability to make predictions on foreign data, it is essential to acknowledge that the model's capability to handle previously unseen data is also impacted by various other factors, including the diversity and representation within the dataset, the complexity of the problem, the architecture, and the model's parameters. However, the suggested approach offers a solid basis for enhancing the model's ability to handle and generalize on unfamiliar data by augmenting the dataset with diverse visual styles.

CONCLUSION

The presented information suggests that generative style transfer can enrich the dataset and improve visual supervised learning. Generative style transfer adds visual variety to a learning dataset by applying a style or aesthetic from one dataset to another. Visual style transfer applications enrich datasets by increasing visual style variety. The model needs many examples in the training data to learn and apply information in supervised learning. Style transfer adds new style variations to the dataset. Texture, composition, and other visual attributes may vary. A dataset with different art styles can help a model that recognizes animal images. The model will learn more about different visual representations of the same object. Style transfer also reduces biases and imbalances in the original dataset, improving its quality. By combining styles or aesthetics from diverse data sources, especially balanced ones, style transfer can improve a dataset's balance and representativeness. This helps create datasets that

*name of corresponding author

better capture visual data variations. Style transfer also improves model interpretation. By adding visual styles to datasets, models can better understand and interpret style differences from different data sources. Style transfer significantly improves supervised learning datasets. Style transfer enhances visual supervised learning by expanding style range, dataset quality, and model interpretability. The proposed approach has the potential to increase models' ability to extrapolate new, previously unencountered data, making them more responsive and adaptable to a broader range of data.

REFERENCES

Cai, Q., Ma, M., Wang, C., & Li, H. (2023). *Image neural style transfer : A review ☆*. *108*(October 2022), 1–12.

Fan, C., Wu, Q., Zhao, Y., & Mo, L. (2024). *Integrating active learning and semi-supervised learning for improved data-driven HVAC fault diagnosis performance*. *356*(October 2023).

Fernandez-fernandez, R., Victores, J. G., Gago, J. J., Estevez, D., & Balaguer, C. (2022). *Neural Policy Style Transfer*. *72*(June 2020), 23–32.

Hindarto, D. (2022). Perbandingan Kinerja Akurasi Klasifikasi K-NN, NB dan DT pada APK Android. *JATISI (Jurnal Teknik Informatika Dan Sistem Informasi)*, *9*(1), 486–503. https://doi.org/10.35957/jatisi.v9i1.1542

Hindarto, D., & Handri Santoso. (2021). Android APK Identification using Non Neural Network and Neural Network Classifier. *Journal of Computer Science and Informatics Engineering (J-Cosine)*, *5*(2), 149–157. https://doi.org/10.29303/jcosine.v5i2.420

Hindarto, D., & Santoso, H. (2022). PERFORMANCE COMPARISON OF SUPERVISED LEARNING USING NON-NEURAL NETWORK AND NEURAL NETWORK. *Janapati*, *11*, 49–62.

Hindarto, D., & Santoso, H. (2023). *PyTorch Deep Learning for Food Image Classification with Food Dataset*. *8*(4), 2651–2661.

Huang, H., Liu, X., & Yang, R. (2021). *Image style transfer for autonomous multi-robot systems*. *576*, 274–287.

Li, J., Wu, L., Xu, D., & Yao, S. (2023). *Knowledge-Based Systems Soft multimodal style transfer via optimal transport*. *271*.

Meng, Y., Yang, Y., Hu, M., Zhang, Z., & Zhou, X. (2023). *Artificial intelligence-based radiomics in bone tumors : Technical advances and clinical application*. *95*(July), 75–87.

R, J. V. C. I. (2022). *Neural Style Transfer for image within images and conditional GANs for destylization*. *85*(March).

Schramm, S., Wehner, C., & Schmid, U. (2023). *Comprehensible Artificial Intelligence on Knowledge Graphs : A survey*. *79*(August).

Taha, A., Saad, B., Taha-mehlitz, S., Ochs, V., El-awar, J., Mourad, M. M., Neumann, K., Glaser, C., Rosenberg, R., & Cattin, P. C. (2023). *Analysis of arti fi cial intelligence in thyroid diagnostics and surgery : A scoping review*. *October*.

Vieira, M., Silva, L. H. F. P., Dantas, J., Junior, D., Cunha, M., Ricardo, A., & Fernando, J. (2023). *Generating synthetic multispectral images using neural style transfer : A study with application in channel alignment*. *206*(January).

Wang, W., Li, Y., Ye, H., Ye, F., & Xu, X. (2023). *Engineering Applications of Artificial Intelligence Ink painting style transfer using asymmetric cycle-consistent GAN*. *126*(October 2022).

Yang, K., Zhao, H., Sun, Y., Liu, Q., & Hu, B. (2022). *KAGAN : A Chinese poetry style transfer method*. *102*(April), 1–11.

Ye, W., Liu, C., Chen, Y., Liu, Y., Liu, C., & Zhou, H. (2023). *Multi-style transfer and fusion of image ' s regions based on attention mechanism and instance segmentation*. *110*(August 2022).

Yuan, Y., Wu, Y., Cheng, J., Yang, K., Xia, Y., Wu, H., Wu, Y., Cheng, J., Yang, K., Xia, Y., Wu, H., & Pan, X. (2023). *Applications of artificial intelligence to lipid nanoparticle delivery*.