Batik-Image Style Transfer Using Neural Style Transfer and Convolutional Autoencoder

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Abstrak

Adanya tantangan pada NN untuk memroses penilaian seni visual selayaknya manusia membuat Gatys et al terinspirasi dan pada tahun 2015 mereka berhasil menciptakan neural style transfer (NST) yang mampu memindahkan gaya gambar artistik eropa ke gambar lain. Pada saat ini, penelitian terkait NST telah banyak dilakukan, tetapi penggunaannya dengan convolutional autoencoder (CAE) sebagai salah satu arsitektur NN yang mampu melakukan kompresi terhadap output NST masih jarang ditemukan. Penelitian ini bermaksud untuk merancang sistem NST dengan CAE sebagai arsitektur tambahan yang bertugas dalam proses kompresi seraya mempertahankan gaya yang di transfer. Sebagai pengganti gambar artistik gaya eropa, digunakan batik sebagai karya artistik asli Indonesia. Gambar hasil NST dan kompresi akan diukur menggunakan metrik evaluasi structural similarity index measure (SSIM). Hasil evaluasi menunjukan bahwa sistem yang dirancang berhasil mendapatkan skor rata-rata SSIM sebesar 0.67 dari 1 dan nilai rata-rata rasio pengurangan ukuran penyimpanan sebesar 37,43% dari ukuran asli. Kemudian, survei menunjukan bahwa kualitas gambar hasil kompresi tergolong cukup baik dengan skor 64,09% dan gambar hasil kompresi cukup bisa digunakan pada bidang pekerjaan masing-masing responden dengan skor 49,09%.

Kata kunci— Neural Networks, Neural Style Transfer, Convolutional Autoencoder, Batik, Structural Similarity Index Measure

Abstract

The challenge of neural networks to process visual art judgments like humans inspired Gatys et al and in 2015 they succeeded in creating neural style transfer (NST) that can transfer European artistic image styles to other images. At present, research related to NST has been widely conducted, but its use with a convolutional autoencoder (CAE) as one of the NN architectures capable of compressing NST output is still rare. This research intends to design an NST system with CAE as an additional architecture in charge of the compression process while maintaining the force transferred. As a substitute for European-style artistic images, batik is used as an original Indonesian artistic work. NST and compression images will be measured using structural similarity index measure (SSIM) evaluation metrics. The evaluation results showed that the system designed managed to get an average SSIM score of 0.67 out of 1 and an average value of storage size reduction ratio of 37.43% from the original size. Then, the survey showed that the quality of the compressed image was quite good with a score of 64.09% and the compressed image was quite usable in the field of work of each respondent with a score of 49.09%.

Keywords— Neural Networks, Neural Style Transfer, Convolutional Autoencoder, Batik, Structural Similarity Index Measure

1. INTRODUCTION

In 2006, a researcher named Geoffrey Hinton managed to create an artificial neural network that he called Deep Belief Nets. The concept of learning this artificial neural network is to train a layer that will be added with a new layer, then train a new layer, and will continue so on. Geoffrey Hinton says that using this strategy makes it possible to train artificial neural networks that already exist and have more layers. His research by Geoffrey Hinton was the beginning of the emergence of the term currently known as Deep Learning. In Deep Learning, there is the term Neural Networks which is a layer of representation inspired by the ability to understand something as done by the human brain. Thus, the concept, of deep learning is intended to have the ability to learn computational methods independently without being assisted by the maker [1].

In the field of psychology, there is a challenge to understand how humans process visual arts judgments. This is because every individual has cognitive abilities that affect how they value and understand a work of art. Although many theories explain how humans understand works of art, there is no single theory that can be computed precisely and accurately [2]. In previous neural style transfer research, many paintings with European style were used, therefore in this study Batik style images will be used as works of art from Indonesia that have existed since ancient times which until now are still being preserved [3]. Batik itself has been inaugurated by UNESCO on October 2, 2009 as a Masterpieces of the Oral and Intangible Heritage of Humanity [4][5].

On this basis, this study intends to implement the Neural Style Transfer (NST) algorithm with Convolutional Autoencoder (CAE) on content images with batik images to combine the two images and produce new images with artistically unique styles. The image will then be processed with CAE so that it has a compressed shape and size while maintaining the transferred force. In addition, the use of NST with sequential CAE for compression process in batik-style image transfer and extracting features from the encoder layer on sequential CAE can be a novelty compared to previous research using autoencoders on voice data and others. Thus, through this research, it is hoped that it can help introduce the application of NST with CAE in making images with a new style of batik theme that has a compressed shape and size while maintaining the style that has been transferred.

2. LITERATURE REVIEW

2.1 Neural Style Transfer

The Neural Style Transfer method was first proposed by Leon A. Gatys, Alexander S. Ecker and Matthias Bethge in their research entitled "A Neural Algorithm of Artistic Style" in 2015. This study discusses how to exchange styles on an image content and style while still maintaining the features of the content using CNN architecture [6]. The basic idea of the Neural Style Transfer (NST) method by Gatys et al is to periodically optimize images by matching the distribution of features obtained from the extraction of each desired convolution layer on a CNN specifically using the VGGNet architecture. This research became the beginning of the NST method. NST's success in creating a new style of drawing attracted the attention of scientists and industry. New research related to NST is widely carried out with the aim of developing using these algorithms [7]

Based on Gatys et al, the objective of this NST method is about how the layers of the CNN architecture such as using VGGNet can retrieve features from input images. Through these experiments, Gatys et al also found that each unit of the convolution layer is capable of working as an image filter and performing feature extraction on the image. The results obtained from each layer are referred to as feature maps [8]. However, simply extracting features is not enough to perform the NST process, therefore a loss function is used to ensure that the captured features can be applied to other images. The loss function is divided into two parts, namely content loss and style loss. There are also other studies that use the loss function, such as those conducted by Majumdar et al who use VGGNet to calculate content loss and style loss at each layer in the VGG model [9].

2.2 Convolutional Autoencoder

According to Manakov et al, Convolutional Autoencoder was first introduced in 2011 by the research team of J Masci, U Meier, D Cireşan, and J Schmidhuber through their paper entitled "Stacked convolutional auto-encoders for hierarchical feature extraction". The initial idea of Convolutional AE was to replace the FC layer on the classic autoencoder with a convolution layer [10]. Then based on Mao et al through their research entitled "Image Restoration Using Very Deep Convolutional Encoder-Decoder Networks with Symmetric Skip Connections" it is stated that their Convolutional AE is formed of several layers of convolution and deconvolution and can learn end-to-end mapping from images that have been deconstructed on the encoder so that they can be reconstructed into the original image. Convolutional AE is not the first to use convolution and deconvolution layers in a single architecture, this method has previously been used for semantic segmentation purposes [11][12][13].

2.3 Batik

Batik is a work of art since ancient times that has been known since the time of the Majapahit kingdom which until now is still being preserved. Batik itself has several manufacturing techniques, namely written batik, painted batik, and stamp batik [3]. The beauty of this unique batik has been used by irresponsible individuals who only want profits by acknowledging that batik is their property or product, both by foreign countries and private companies [14].

2.4 Structure Similarity Index Method

Images that have passed through various stages of image processing have the potential to lose their information because the process makes the image distorted. Therefore, an algorithm is needed that can provide quality assessments automatically and consistently like assessments that can be done by humans [15]. The structural similarity index method or SSIM is a model made with the concept of perception. This method assumes that changes such as degradation in images are changes in the perception of structural information. The structural information in question is an image pixel that is dependent (inter-dependent pixel) or a pixel that is spatially closed. SSIM works by estimating through estimating the quality of an image or video between the original image or video and another image or video. Through her research, Sara et al mentioned that SSIM comparatively has advantages over the Mean Square Error (MSE) and Peak Signal Noise Ratio (PSNR) metrics [16]. The use of SSIM has been widely spread for almost two decades and it plays an important role in the task of assessing image quality in various aspects of research [17]. In quality measurement using SSIM, there are three main aspects consisting of luminance, contrast, and structural or correlation terms [18].

2.5 Likert Scale

The Likert scale was first introduced by psychologist Rensis Likert in 1932. This scale uses psychometric concepts that are commonly used in various fields that require surveys and require using of questionnaires in taking votes from respondents. The rating scale of the Likert scale contains negative or positive responses. There are several ranges of scales commonly used by social science researchers, namely the scale of three, five, seven, or nine. Odd numbers are preferred by such researchers because they want to know the neutral response of respondents. On the other hand, some studies use odd scales on Likert scales. This scale is used to avoid neutral response scenarios on surveys. On the Likert scale that uses a scale of five, the value 1 represents a very negative response, then on a scale of 5 represents a very positive response [19].

2.5 Related Works

Qian et al in their research entitled "Autovc: Zero-shot voice style transfer with only autoencoder loss" stated that generative adversarial networks (GAN) model training has a complicated and difficult level of training and there is no strong evidence that GAN is able to produce good output quality perceptually, so Qian et al chose to use a deep style transfer algorithm approach with a simple autoencoder, Because according to their research, simplicity in an autoencoder will not be a bad thing as long as the architectural design is carefully constructed and able to make a difference [20].

Li et al in their research entitled "SE-DAE: Style-Enhanced Denoising Auto-Encoder for Unsupervised Text Style Transfer" combines style transfer and denoising autoencoder (DAE) techniques on text data to change the style of the text while maintaining the semantic meaning of the text and training it to produce novel-like sentence styles. Through his research as well, it is mentioned that the use of the autoencoder is able to remove noise from the output produced while maintaining the original information / content [21].

Gupta et al in their research entitled "Characterizing and improving stability in neural style transfer" stated that the use of style transfer with the real time method can result in unstable results and leave flickering that is very visible in the output so they propose the use of recurrent convolutional network for real time style transfer cases. In its development, Gupta et al used the structural similarity index measure (SSIM) evaluation metric to recognize unstable characters in previous methods and thus they can produce objective solutions [22].

Ayub and Wagner in their research entitled "Storing encoded episodes as concepts for continual learning" use neural style transfer and convolutional autoencoder (CAE) to overcome continual learning problems such as catastrophic forgetting or forgetting and storage memory limitations for data. By using the two-algorithm approach, Ayub and Wagner succeeded in overcoming the problem of catastrophic forgetting during the classification process in continual learning due to data degradation, especially complex ones using neural style transfer, in addition, memory usage was also successfully suppressed even to reduce 78% of the original speech [23].

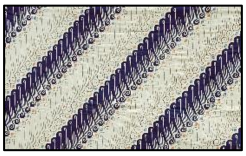
3. RESEARCH METHODOLOGY

3.1 Dataset

For content images, it will be taken from Freepik which is the work of the author called wirestock with free-to-use and non-commercial properties. For batik images, a dataset is used by a Kaggle user with an id named dionisiusdh. There will be 20 batik images, each of which has different motifs, namely Balinese, Betawi, Celup, Cendrawasih, Ceplok, Ciamis, Garutan, Gentongan, Kawung, Keraton, Lasem, Megamendung, Parang, Pekalongan, Priangan, Sekar, Sidoluhur, Sidomukti, Sogan, and Tambal. The following is Table 1 which shows the content and batik images.

Table 1. Content and Batik Images

 Content Image	 Balinese Batik	 Betawi Batik

 Celup Batik	 Cendrawasih Batik	 Ceplok Batik
 Ciamis Batik	 Garutan Batik	 Gentongan Batik
 Kawung Batik	 Keraton Batik	 Lasem Batik
 Megamendung Batik	 Parang Batik	 Pekalongan Batik
 Priangan Batik	 Sekar Batik	 Sidoluhur Batik
 Sidomukti Batik	 Sogan Batik	 Tambal Batik

3.2 Model Design

The model designed will contain 3 main functions, namely NST which functions to produce styled images an extracted encoder which functions to produce feature map images, and AE which functions to reconstruct feature maps into new images in compressed form. After the three types of images are obtained, it will proceed with evaluating the similarity of the structure with SSIM metrics, evaluating storage size, and also used surveys that will ask the quality of the resulting image and the capabilities of the image when used on the job. Below is Figure 2 which shows the model design of the system.

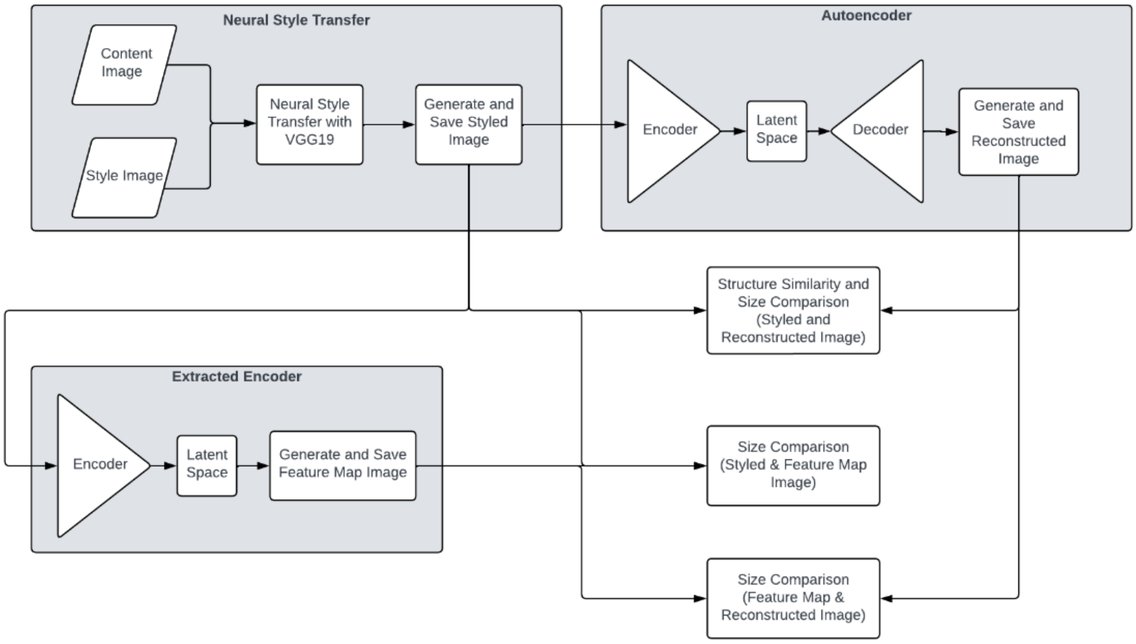


Figure 2. Model Design Diagram

3.3 Training Details

In the style transfer training, hyperparameters are used in the style transfer function, namely steps of 5000, content weight or alpha of 1, style weight or beta of 1e6, style gram matrix weights consisting of conv1_1 of 1.2, conv2_1 of 0.80, conv3_1 of 0.25, conv4_1 of 0.25, conv5_1 of 0.25 and learning rate for Adam optimizer of 0.01. For compression with CAE, hyperparameters to be used on the training will use 2 convolution layers on the encoder and decoder and 1000 epochs. Below is Table 2 which shows the CAE layers.

Table 2. Convolutional Autoencoder Layers

Layer	Output Shape	Type
Input	224x224x3	Encoder
Conv2D + ReLu	224x224x16	Encoder
MaxPooling2D	112x112x16	Encoder
Conv2D + ReLu	112x112x8	Encoder
MaxPooling2D	56x56x8	Encoder
Conv2D + ReLu	56x56x8	Decoder
UpSampling2D	112x112x8	Decoder
Conv2D + ReLu	112x112x16	Decoder
UpSampling2D	224x224x16	Decoder
Conv2D + Sigmoid	224x224x3	Decoder

3.4 Evaluation

For the evaluation stage, the Structure Similarity Index Method (SSIM) metric is used to measure the difference between the image from the transfer of force and the image compressed by the autoencoder. SSIM has a range of values between zero and one, if the calculation results produce a score of one, it means that the image has a perfect resemblance to the comparison image, and vice versa if the score is zero then the target image does not have any resemblance to the target image. In addition to using SSIM, the size difference in styled image, feature map, and reconstructed image will be calculated to see how efficient the model is in compressing image size. Then, a survey was also conducted on the level of respondents' satisfaction with the results of compressed images and the capabilities of their application images in the respondent's field of work on a scale of one to five. The following is Table 3, which contains values and representations of answers on a five-point Likert scale [24].

Table 3. Five-Point Likert Scale

Answer	Representation Value	Interval
1	Strongly Disagree	0% - 19,99%
2	Disagree	20% - 39,99%
3	Neutral	40% - 59,99%
4	Agree	60% - 79,99%
5	Strongly Agree	80% - 100%

4. RESULTS AND DISCUSSION

4.1 Evaluation

The following are Figure 3 and Figure 4 which showing the test results of the style transfer and compression with CAE functions using content images and styles.

Figure 3. Style Transfer Output


Figure 4. Compressed Output

The image storage size evaluation stage is carried out after passing the encoder function to styled images with feature maps images obtained by extracting values in the latent space after passing through the latest encoder layer.

Table 4. Results of Stylized Image Size Evaluation with Feature Maps

Batik Type	Styled Image Size (KB)	Feature Map Size (KB)	% Size Difference from Styled
Bali	19,70	23,80	120,81
Betawi	17,80	21,49	120,73
Celup	16,70	21,80	130,51
Cendrawasih	19,60	23,54	120,10
Ceplok	15,50	21,24	137,03
Ciamis	19,20	23,63	123,07
Garutan	17,00	20,25	119,14
Gentongan	14,50	18,42	127,06
Kawung	13,00	17,80	136,95
Keraton	21,10	25,30	119,91
Lasem	18,20	21,65	118,93
Megamendung	15,50	22,92	147,87
Parang	15,20	19,15	125,99
Pekalongan	23,40	24,11	103,03
Priangan	19,80	21,84	110,30
Sekar	20,50	21,20	103,43
Sidoluhur	19,70	22,27	113,05
Sidomukti	19,80	22,00	111,11
Sogan	18,70	20,67	110,53
Tambal	19,50	23,37	119,85
Average	**18.22**	**21.82**	**120.97**

In the Table 4 above, it can be seen that the styled image that passes through the encoder will have a larger total size than the beginning, this is normal considering the feature map image has two dimensions so that it will have a grayscale base color and a total of eight images. This feature map image will then be forwarded to the decoder to be reconstructed to its original size of 224x224x3. The following is Table 5 which shows the evaluation of storage size between feature maps images with compressed images or decoded output.

Table 5. Results of Feature Map Size Evaluation with Compressed Image

Batik Type	Feature Map Size (KB)	After Compression Size (KB)	% Size Difference from Feature Map
Bali	23,80	12,30	51,68
Betawi	21,49	11,30	52,58
Celup	21,80	12,60	57,81
Cendrawasih	23,54	11,60	49,28
Ceplok	21,24	9,98	46,99
Ciamis	23,63	11,10	46,97
Garutan	20,25	9,48	46,81
Gentongan	18,42	7,28	39,52
Kawung	17,80	9,10	51,11
Keraton	25,30	14,20	56,13
Lasem	21,65	12,40	57,29
Megamendung	22,92	12,40	54,10
Parang	19,15	9,52	49,71
Pekalongan	24,11	13,50	55,99
Priangan	21,84	12,30	56,32
Sekar	21,20	11,40	53,77
Sidoluhur	22,27	12,10	54,33
Sidomukti	22,00	12,20	55,46
Sogan	20,67	10,10	48,86
Tambal	23,37	12,10	51,78
Average	**21.82**	**11.35**	**51.82**

Based on Table 5, it can be seen that the process of combining the eight feature maps to produce a 224x224x3 image has a smaller size than the styled image that is the input encoder. This can be seen from the difference between the average styled image which is 21.82 KB and the average image after decoder reconstruction which is 11.35 KB. After generating all styled images, feature maps, and reconstructed images, an evaluation of the size of styled images with images that have been reconstructed by CAE is shown in Table 6 below.

Table 6. Results of Stylized Image Size Evaluation with Compressed Image

Batik Type	Styled Image Size (KB)	After Compression Size (KB)	% Size Reduction
Bali	19,70	12,3	37,56
Betawi	17,80	11,3	36,52
Celup	16,70	12,6	24,55
Cendrawasih	19,60	11,6	40,82
Ceplok	15,50	9,98	35,61
Ciamis	19,20	11,1	42,19
Garutan	17,00	9,48	44,24

Gentongan	14,50	7,28	49,79
Kawung	13,00	9,10	30,00
Keraton	21,10	14,2	32,70
Lasem	18,20	12,4	31,87
Megamendung	15,50	12,4	20,00
Parang	15,20	9,52	37,37
Pekalongan	23,40	13,5	42,31
Priangan	19,80	12,3	37,88
Sekar	20,50	11,4	44,39
Sidoluhur	19,70	12,1	38,58
Sidomukti	19,80	12,2	38,38
Sogan	18,70	10,1	45,99
Tambal	19,50	12,1	37,95
Average	**18.22**	**11.35**	**37.43**

Based on the results in Table 6 above, it is known that the size of the transfer style image before the compression process with the largest CAE is the pekalongan batik styled image with a size of 23.4 KB, and the smallest transfer style image is the kawung batik styled image with a size of 13 KB. Then after using the CAE compression function, the smallest compressed image size is owned by gentongan batik with a size of 7.28 KB, and the largest compressed image is owned by palace batik with a size of 14.2 KB. For the average value, the average size of the image before compression or using only the transfer style was 18.22 KB, the average size of the image after passing the compression function with CAE was 11.35 KB, the average percentage of the original size was 62.57% and the average size reduction ratio was 37.43%.

4.2 Model Evaluation

Model evaluation is done with SSIM measurement metrics and Likert scale.

4.2.1 SSIM

After all images have passed the style transfer and compression stages with CAE, then the image will be evaluated using SSIM measurement metrics between the style transfer image and the CAE compressed image.

Table 7. Image Evaluation With SSIM

Batik Type	SSIM Score	Average
Bali	0,70	**0.67**
Betawi	0,65	
Celup	0,85	
Cendrawasih	0,62	
Ceplok	0,76	
Ciamis	0,51	
Garutan	0,57	
Gentongan	0,51	
Kawung	0,75	
Keraton	0,79	
Lasem	0,74	
Megamendung	0,85	
Parang	0,67	
Pekalongan	0,61	

Priangan	0,65	
Sekar	0,59	
Sidoluhur	0,70	
Sidomukti	0,61	
Sogan	0,55	
Tambal	0,64	

Based on the results in table 7 above, it is known that the smallest SSIM score is owned by gentongan and ciamis batik images with a score of 0.51 out of 1, and the largest SSIM score is owned by megamendung and celup batik image with a score of 0.85 out of 1. The average score of all SSIM results above is 0.67 out of 1.

4.2.2 Likert Scale

After calculating the evaluation using SSIM, the next step is the evaluation using the Likert scale. This evaluation will use a survey distributed to 44 people as respondents who will fill out a survey about the level of respondents' satisfaction with the results of compressed images and the capabilities of image application in the respondent's field of work on a scale of one to five. Respondents were divided into two groups, the first group or K1 is a group that has a non-graphic design or illustration or game field of work, while the second group or K2 is a group that has a field of work related to graphic design or illustration or games. Of the 44 responses obtained, it is known that 38.6% or 17 people are K1 while the remaining 61.4% or 27 are K2. The following is a general percentage calculation of 44 respondents shown in the form of the following Table 8.

Table 8. General Respondents

Score	Compressed Image Quality (Q1)
1	2
2	13
3	9
4	14
5	6
Total	**44**

Based on the results above, it is known that the Q1 score is 64.09%m so it can be concluded that respondents as a whole answered that the compressed image has a relatively good quality when compared to raw images. Then in the Q2 answer, the score obtained was 49.09% so it can be said that respondents as a whole answered that the compressed image can be used enough in their respective fields of work.

After getting a percentage score in general, a percentage score calculation was also carried out for each K1 and K2 group. The response of K1 or groups who have non-graphic design or illustration or game work to Q1 and Q2 in the form of the following Table 9.

Table 9. K1 and K2 Response

Score	K1 Response		K2 Response	
	Compressed Image Quality (Q1)	Image capabilities for use in jobs (Q2)	Compressed Image Quality (Q1)	Image capabilities for use in jobs (Q2)
1	0	9	2	8
2	3	1	10	5

3	2	3	7	6
4	7	3	7	5
5	5	1	1	3
Total	**17**	**17**	**27**	**27**

Based on the table 9 section K1 response, known that the Q1 score is 76.47% so it can be said that K1 in general answers the compressed image has good quality when compared to raw images. Then in the Q2 answer, the score obtained was 43.53% so it can be said that K1 in general answered that compressed images are enough to be used in their field of work. Then, based on the table 9 section K2 response, it is known that the Q1 score is 56.30% so it can be said that K2 in general answers the compressed image has a fairly good quality when compared to the raw image. Then in the Q2 answer, the score obtained was 52.59% so it can be said that K2 in general answered that compressed images are enough to be used in their field of work.

5. CONCLUSION

In this paper, a neural style transfer system with a convolutional autoencoder is proposed as an additional model to perform the image compression process while maintaining the image style. based on the results of the evaluation with SSIM, it is known that the average score obtained is 0.65 out of 1. Then, when viewed from the compression ratio, the average value of the storage size reduction ratio is 37.43%. Based on the results of the evaluation of the size and similarity of the structure that has been carried out previously, it can be concluded that the model used is able to carry out its role in reducing the size of the image storage while maintaining the transferred style. Then on the evaluation score using the Likert scale, based on 44 responses obtained through the survey, it is known that the percentage score obtained on questions about the quality of compressed images on raw images is 64.09% or quite good when compared to raw images, while for questions about the capabilities of compressed images for their application in their respective fields of work, a percentage score of 49.09% is obtained which means that in general, compressed images can be used in their respective fields of work.

6. SUGGESTION

To improve the performance of this model, there are several approaches that can be used such as Hyperparameter tuning on the convolutional layer used by the convolutional autoencoder model so that it is able to strengthen features when reconstructing images on the decoder. Strengthening the features in question such as lines, colors, or specific textures considering the compression process can reduce the quality of important features in the image, Using regularization methods such as weight decay, converting per-pixel-loss techniques commonly used in neural style transfer into perceptual loss, and utilizing more feature maps extracted from styled images in enhanced encoders as encryption keys that store uniqueness in the resulting image so that Can maintain the uniqueness of the motives formed so that they are not misused and freely owned.

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