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Improving Image Quality to Assist Brand Logo Detection in Blurred Images

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Abstract

Logo detection is a challenging task in computer vision, especially when the logos are blurred or distorted in the images. Image deblurring is a technique that can improve the quality and clarity of the logos, which can enhance the logo detection performance. In this paper, we propose a novel method for logo detection that combines image deblurring and robust logo detection techniques. We create synthetic blurred images from the Flickr Logos 27 Dataset using Motion Blur data to improve deblurring methods. Then, we use three different image deblurring methods, namely Restormer, DeblurGAN-v2, and DeepRFT, to preprocess the images and remove the blur effects to improve the sharpness of images. We then use two different logo detection methods, namely Yolov7 and Robust Logo Detection, to detect and recognise the logos in the images. We evaluate our method on the Flickr Logos 27 dataset, which is a well-known and widely used dataset for logo detection. It contains 810 annotated images of 27 logo classes, as well as 4207 distractor images and 270 query images. We show that combining the method of Robust Logo Detection with Restormer achieves the highest mean average precision (mAP) at 0,754 among all the methods, and significantly improves the logo detection accuracy on blurred images. We conclude that image deblurring can effectively enhance logo detection performance and that our method is the best combination of image deblurring and logo detection techniques.

Keywords: *logo detection, deblurring method, image enhancement, deep learning, flickr27 dataset*

1. Introduction

A logo is a visual and textual sign used to identify a brand and elements of a product. The logo design is an important decision in marketing to encourage user decisions and performance about the products [1]. The logo on a product image can provide additional information about the product itself. Logo recognition uses points of coordinates in an image and creates the bounding box, after the bounding logo is identified it continues to detect a logo in the bounding box [2]. To enhance logo detection, it can improve brightness like light correction, and correct image distortion. It makes the logo detection more accurate [3]. In the forensic world, a logo can be used as evidence. Police investigators can quickly identify clothes logos or other objects with suspected people [4]. One of the problems in logo detection in the forensic world is if the logo has a blurred image, a mechanism is needed to repair the logo before detection is carried out. Blur logo detection can be applied to surveillance and security applications to help investigators identify suspects, cars, or objects at a crime scene. It can help to investigate criminal investigations based on the clothes logo [4]. This detection can be applied for logo detection in moving vehicles [5]. This research using the deblurring process in the logo detection process can help identify the logo when it is blurry. Many blur logo detection helps the identification of moving logos [6], [7].

There are many methods for logo detection with blurred images that do preprocessing before detecting a logo. From [2] scale the image to improve logo detection, from [3] logo image will be enhanced before being processed for logo detection, and from [4] train the

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model with a blurred image to help the model detect the logo on the blurred or low-light image.

Preprocessing a logo image while the image is not of good quality is for improvement the image information is not lost when logo detection [4], [5], [6]. This strategy is important to detect the logo more accurately. After preprocessing, the image will be processed into a logo detection model. Each model has a strategy for logo detection in blurred images which is the best combination of the preprocessing image method and logo detection model. Preprocessing and logo detection model strategies are important for logo detection to be more accurate. From the preprocessing strategy, there are methods for image deblurring to approach blurred images before the logo detection step.

There are many types of causes of blurred images [8], they are motion blur, out-of-focus blur, gaussian blur, and mixed blur. Previous researchers have solutions for those types of causes [9]–[12] to deblur the image and have a better quality image.

In this paper, our study finds the best preprocessing and logo detection model combinations. The results are divided into two parts. First, the image will undergo the deblurring process, where a model trained to recognise blurry images will produce a restored image that will improve the quality of a logo image. Then, the processed images will be detected by a logo detection model that has been trained on a deblurring dataset. Using deblurring logo detection can improve logo detection in blurred images. Materials and Methods given in section 2 are about data acquisition, review method, and finding the best combinations from each method. Results and Discussion in section 3 are about obtained combination results and discussion of a new combination for improvement logo detection in the blurred image; the last is a conclusion.

2. Research Methodology

In this paper, our research will combine preprocessing images with an image deblurring method and logo detection. This research will review logo detection performance before using image deblurring methods.

Our research uses image deblurring methods for preprocessing specifically Deblur Generative Adversarial Network-v2 (DeblurGAN-v2) [13], Restoration Transformer (Restormer) [14], Deep Residual Fourier Transformation for Single Image Deblurring (DeepRFT) [15] and logo detection methods specifically YOLOv7 [16], [17], Robust Logo Detection [18]. We used the synthetic data from the FlickrLogos-32 [19] dataset and created the blurred images from the Gaussian blur effect.

We combined preprocessing and logo detection methods with previous research and searched for the best combination. We limit the method to experiment due to the limitation of our resources. Our research will compare the best preprocessing performance from our review in image deblurring and logo detection. In image deblurring our review uses the best Structural Similarity Index Measure (SSIM) and Peak Signal to Noise Ratio (PSNR) after processing the blurred images. Our review uses the best Mean Average Precision (mAP) in logo detection.

In the first phase, we review the preprocessing with image deblurring methods. There are three methods we review, the first is DeblurGAN-v2 [13], the second is Restormer [14], and the third is DeepRFT [15]. DeblurGAN-v2 is a state-of-the-art image deblurring method that applies the generative adversarial network (GAN), the method used Feature Pyramid Network (FPN) is a combination of a single feature map and pyramidal feature hierarchy [20]. This method is used to detect images as objects with various scales. The next method is Inception-ResNet-V2 [21] tested for the best visual quality in DeblurGAN-v2. Use the PatchGAN [22] discriminator to create a sharper result than DeblurGAN [23]. The PatchGAN discriminator patches the image with a size of 70x70 [22]. DeblurGAN-v2 using the GoPro dataset [23] with the performance of this method measured by PSNR 29,55 and SSIM 0,934 [13]. In Figure 1, this is a process for DeblurGAN-v2. On the Pretrained backbone process, there are convolution blocks and a max pooling layer after that continue with 1x1 convolution for every convolution block in the pretrained backbone. After that, processed in the upsampling layer in 2,4,8 continues with an additional layer and the concatenation layer is to concat the result from an earlier layer. After that, element-wise addition is computation added from the image input layer with the concatenation layer and the result is the output.

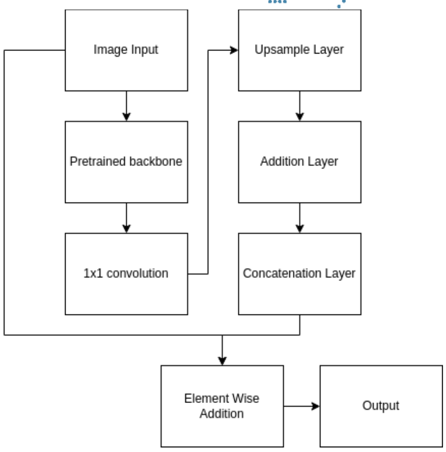

Figure 1. DeblurGAN-v2 methodology [13].

The second is the Restormer novel method, this method has three core components. The first component is Multi-Dconv Head Transported Attention (MDTA), this component in the transformer building block helps to get the attention map from the projected key and query. It is achieved when using 1x1 convolution with aggregation of cross channel [14]. The second component is a feed-forward network (FN) [24] in another transformer building block with two fully connected layers with nonlinearity. The layers have a gating mechanism for enhancing the information to focus on the more refined image attributes. The third component is Progressive Learning, which has smaller image patches in the early stage of the epoch and later progressive larger image patches. It helps to maintain processing time for every optimization [14]. Restormer using the GoPro dataset [23] with the performance of this method measured by PSNR 32,92 and SSIM 0,961 [14]. In Figure 2, this is a process in the Restormer method. First, image input is consumed with element-wise addition and convolutional 3x3. After that continue it with transformer block with downsampling and upsampling. In upsampling flow they are Multi-DConv Head Transposed Attention and Gated Dconv Feed Forward Network. After that continue it with concatenation for every transformer block. In element-wise addition, there are computational additions from image input and the processed result. In Figure 2, there is a Restormer process. First, the image input is processed to convolution 3x3, after that, it continues to transformer block

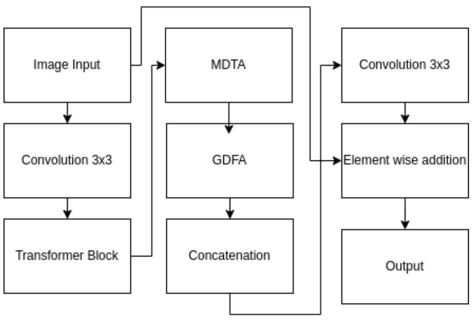

Figure 2. Restormer methodology [14].

The third is the Deep-RFT novel method, this method uses the Residual Fast Fourier Transform with a ReLU activation block because it can increase the PSNR with a specific

ReLU threshold [15]. The method is combined with other models and achieves the best result with MIMO-Unet [25] and NAFNet32 [26]. Deep-RFT using the GoPro dataset [23] with the performance of this method with FNAFNet64 by PSNR 33,85 and SSIM 0,967. In Figure 3 this is a process in the Deep-RFT method. First, there are many input images with different heights, widths, and channel sizes. After that, the image is processed Depth-wise Over Convolution (Do-Conv) with 3x3 convolution. This Step applies the single convolutional layer to each input layer. After that, we split into three encoder blocks. The first encoder block will process with Residual Fast Fourier Transform (Res FFT) only. Res FFT will process images with computation Residual and FFT algorithm to reduce computation complexity from Discrete Time Fourier Transform (DFT). The second and third encoder blocks are Do-Conv, Res FFT, and Feature Attention Module. The Feature Attention Module is a refined feature in the image there are processes for every embedding feature, and after that pooling the convolution and multiplies it with a feature correlation matrix [31]. The second, output from the encoder block will processed in Attentional Feature Fusion (AFF) [33]. After that, it continues with Concatenation. It concat with the decoder block from Res FFT and Transpose Conv, decoder block Do-Conv, Res FFT-Conv blocks, and Transport Convolution with other AFF. It outputs the restored images.

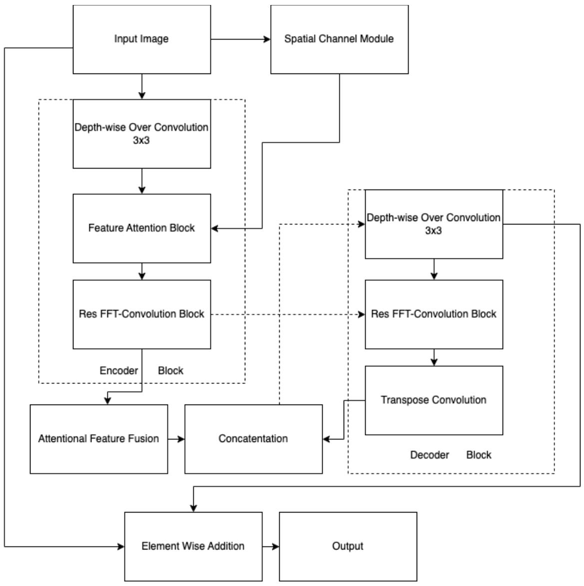

Figure 3. Deep-RFT methodology [15].

In the second phase, we reviewed the logo detection and tested the method with the result from a preprocessing image. There are two methods we review. The first is Robust Logo Detection using the method DetectoRS. This method detects the objects with Recursive Feature Pyramid and Switchable Atrous Convolution [27]. It makes this method robust for adversarial attacks. It is implemented by adding some improvements to change DetectoRS into cascade DetectoRS, using the method Equalization Loss [28], and creating the adversarial data augmentation image to improve the accuracy of the model [18]. This method experimented using a dataset Open Brands [30] with the performance of this method measured by mAP 0,6508. In Figure 4 this is a process in the Robust Logo Detection method. First, the image is input into the method, and after that, the image is processed with a Recursive Feature Pyramid (RFP). After that, with backbone ResNet50. There are the bottom-up backbone and top-down feature pyramid networks. These backbone layers process images twice or more at the macro level and output the prediction. The prediction is processed by Switchable Atrous Convolution (SAC) to decide the input features different atrous rates and the outputs combined with the switch. In SAC there are three components. The first is the pre-global context. This input is split into two, first to Global Average Pool and processed to convolution 1x1. second is straight to addition with output another segment. second is the main function of SAC. There are three segments. The first segment is to convolution 3x3 with atrous 1, second segment is average pool 5x5 and convolution 1x1. third is convolution 3x3 with atrous 3. The first and third convolutions have the same weights. The three segments are output and have additions for the segment. The last component is post-global context, which is the same as the first components but these components have an output.

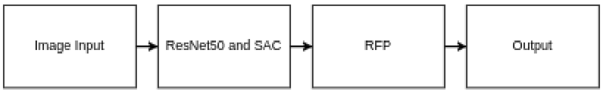

Figure 4. Robust Logo Detection Methodology [18].

The second is that YOLOv7 is a real-time object detection, the difference with an earlier version of YOLO is this method scales up the depth of the computation block 1.5 times and scales up the width of the transition block 1.25 times. This method of the experiment has a better result of average precision, less computation and parameters and added Extended Efficient Layer Aggregation Network (E-LEAN) [16]. This method experimented with logo detection [17] using the dataset Flickr-27 [29] with the performance of this method measured by mAP 0,674. In Figure 5. this is a process in the YOLOv7 method. First, the image is input into the method. Second, in the image processed in Backbone, there are convolution blocks and upsample blocks Third, the neck is like a feature pyramid network. It has a convolution 1x1, convolution block, and upsample block. Fourth there is the head. Convolution and output result in the detection of objects and are calculated with cross-entropy loss, L1 loss, and Objectness loss.

Figure 5. YOLOv7 Methodology [16].

From our review, the proposed method conducted in this study is shown in Figure 6.

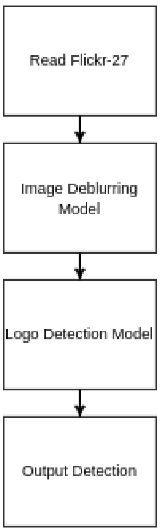

Figure 6. Overview of the Proposed Method

Logo Images: This stage is a selection of logo images, and creates the synthesis to blurred images. We chose the Flickr-27 which has 27 classes with bounding box logo labels in images and various sizes of images [29]. After identifying every image in Flickr-

27 and doing the cleaning dataset to verify the bounding box is available and valid, we create the synthesis image from the Flickr-27 image and make motion blur effects. These effects are applied to every image in Flickr-27 with the same filter. The synthesis image is to experiment with the performance of preprocessing images and create sharp images.

Image Deblurring Model: This stage is preprocessing before being processed for logo detection to enhance the detection of the logo with blurred images. Our research trains the model with synthetic blurred image data tests the model and calculates the performance using PSNR and SSIM. In this stage, we find the best performance and combine it with the logo detection model. There are three methods to test, the first is DeblurGAN-v2, the second is Deep-RFT, and the third is Restormer.

Logo Detection Model: This stage is the main purpose of logo detection with preprocessing. Our research tests two methods, they are YOLOv7 and Robust Logo Detection. Our test wants to get the performance of mean average precision (mAP), We tested with 8 combinations of output preprocessing. First, we tested without preprocessing for YOLOv7 and directly with Flickr-27. Second, we tested without Robust Logo Detection and directly with Flickr-27. Third, we tested with the preprocessing method DeblurGAN-v2 output and tested using the YOLOv7. Fourth, we tested with the preprocessing method DeblurGAN-v2 output and tested using the Robust Logo Detection. Fifth, we tested with the preprocessing method Restormer output and tested using the YOLOv7. Sixth, we tested with the preprocessing method Restormer output and tested using the Robust Logo Detection. Seventh, we tested with the preprocessing method Deep-RFT output and tested using the YOLOv7. Eighth, we tested with the preprocessing method Deep-RFT output and tested using the Robust Logo Detection. The list of combination tests is shown in Table 1.

Table 1. List of Combinations Preprocessing and Logo Detection

Preprocessing	Logo Detection
No Image Deblurring Method	YOLOv7
No Image Deblurring Method	Robust Logo Detection
Restormer	YOLOv7
Restormer	Robust Logo Detection
Deep-RFT	YOLOv7
Deep-RFT	Robust Logo Detection
DeblurGAN-v2	YOLOv7
DeblurGAN-v2	Robust Logo Detection

3. Results and Discussion

The Our research chooses Flickr-27 for experiment preprocessing and logo detection. This dataset has 27 classes of logos with the criteria being various topics for the logo not only specific objects like phones and being able to search proportional test images in natural environments. Every image has a map to the bounding box label, in one image has or more bounding box labels. This dataset has 4207 distractor images, similar to the annotated class images [29]. This dataset has a logo like in Figure 7.

Figure 7. Sample Data in Flickr-27 [29].

After we observed the dataset, we applied the Gaussian blur. Our research chose a mild blur effect with an 11x11 kernel Gaussian blur. This effect is applied to the image and makes the image have a mild blur in Figure 8. We applied the same kernel size to all images in the dataset.

Figure 8. Original and Blurred images after applying the Gaussian effect.

We split the original dataset and the blurred dataset. The original dataset was used when comparing with blurred and then calculating the PSNR and SSIM in the Image Deblurring Model. Our original and blurred dataset split with a ratio of 60% training, 20% validation and 20% testing. This ratio was chosen because of the test in one method of the Logo Detection model in an original state of images with the same random state in the code. In the 300th iteration using the YOLOv7 Logo Detection method, our mAP result with a ratio of 70% training, 30% testing and an Intersection of Union (IoU) value of 0.5 is 0.59. The better result when using a ratio of 80% training, 20% testing and IoU 0.5 are 0.663.

In this section, our research is split into train and test for every method. There are three methods to test it with the original and blurred dataset. We split the result with training and testing. In Table 2. Restomer has a better performance than the other two methods DeblurGAN-v2 and Deep-RFT.

Table 2. Comparison of Preprocessing Method during training

Method	**PSNR**	**SSIM**
Restormer	29.83	0.9346
DeblurGAN-v2	27.30	0.8023
Deep-RFT	26.79	0.7701

Table 3. reveals the performance gap between Restormer and the other two methods. Restormer has the highest PSNR and SSIM values among the three methods, with 29.03 and 0.8706 respectively. Restormer can produce the most accurate and visually pleasing images from blurred input. DeblurGAN-v2 has the second-highest PSNR and SSIM values, with 27.30 and 0.8023 respectively. This suggests that DeblurGAN-v2 can also generate satisfactory results but not as good as Restormer. Deep-RFT has the lowest PSNR and SSIM values, with 26.79 and 0.7701 respectively. This implies that Deep-RFT in our research has the worst performance among the three methods, and its output images may have more noise and distortion than the other two methods.

Table 3. Comparison of Preprocessing Method during testing

Method	**PSNR**	**SSIM**
Restormer	29.03	0.8706
DeblurGAN-v2	24.11	0.7628
Deep-RFT	23.52	0.7086

Restormer has a better performance than the other two methods like the training. The superiority of this method is that it incorporates a self-attention mechanism that enables the model to capture long-range dependencies and global context information from the input images. This allows the Restormer better to preserve semantic and spatial details from blurred images and the Restormer can effectively learn the difference between the blurred and sharp images.

Table 4. reveals the performance metrics of various combinations of preprocessing and logo detection methods on a dataset of images containing logos. The preprocessing methods are Original, Blur, Restormer, Deep-RFT, and DeblurGAN-v2. The logo detection methods are YOLOv7 Logo Detection and Robust Logo Detection. The performance metrics are mean Average Precision (mAP) for both the training and testing phases.

Table 4. List of Combinations Preprocessing and Logo Detection

Dataset	**Logo Detection Method**	**mAP train**	**mAP test**
Original	YOLOv7 LD	0.743	0.63
Original	Robust LD	0.74	0.71
Blur	YOLOv7 LD	0.69	0.647
Blur	Robust LD	0.762	0.745
Restormer	YOLOv7 LD	0.697	0.658
Restormer	Robust LD	0.771	0.754
DeepRFT	YOLOv7 LD	0.602	0.685
DeepRFT	Robust LD	0.744	0.733
DeblurGAN-v2	YOLOv7 LD	0.617	0.593
DeblurGAN-v2	Robust LD	0.735	0.727

The first set of data shows the results of applying the two logo detection methods on the blur dataset, which is obtained by applying the two logo detection methods on the original dataset, which is unaltered. Robust Logo Detection outperforms YOLOv7 Logo Detection in both training and testing phases, with mAP scores of 0.74 and 0.71 respectively, compared to 0.743 and 0.63 for YOLOv7 Logo Detection. It also explains that this indicates that Robust Logo Detection is more accurate and reliable in identifying logos from the original images, while YOLOv7 Logo Detection performs better during the training phase but drops in performance during the testing phase.

The performance of two logo detection methods on the blur dataset is obtained by applying a blurring effect to the original images. It reveals that Robust Logo Detection outperforms YOLOv7 Logo Detection in both training and testing phases, with mAP scores of 0.762 and 0.745 respectively, compared to 0.69 and 0.647 for YOLOv7 Logo Detection. It also highlights that Robust Logo Detection shows a performance improvement compared to the Original Dataset, while YOLOv7 shows a decline. It then interprets that this suggests that Robust Logo Detection is more robust and adaptable to the blurring effect than YOLOv7 Logo Detection and that the blurring effect reduces the quality and clarity of the images.

Another dataset is the performance of two logo detection methods on the Restormer dataset, which is obtained by applying a preprocessing method called Restormer to blurred images. Restormer is designed to restore the sharpness and clarity of the blurred images. It demonstrates that YOLOv7 Logo Detection performs better on the Restormer dataset than on the blur dataset. With mAP scores of 0.75 and 0.72 in the training and testing phase respectively. Robust Logo Detection still outperforms YOLOv7 Logo Detection with mAP scores of 0.763 and 0.75 for the training and testing phases, respectively. It then explains that this indicates that Restormer is an effective preprocessing method for improving the performance of both logo detection methods, but especially for YOLOv7 Logo Detection, which benefits especially from enhanced quality and clarity of images.

The next dataset performance of two logo detection methods on the DeepRFT dataset is obtained by applying a preprocessing method called DeepRFT to the blurred images. DeepRFT is another method for restoring blurred images, but it uses a different approach than Restormer. It shows that YOLOv7 Logo Detection performs worse on the DeepRFT dataset than on the blur dataset, with mAP scores of 0.74 and 0.69 for the training and testing phases, respectively. Robust Logo Detection also performs worse on the DeepRFT dataset than on the blur dataset, with mAP scores 0.76 and 0.74 for the training and testing phases, respectively. It then argues that this indicates the DeepRFT is not a suitable preprocessing method for improving the performance of either logo detection method, and that it may even harm the quality and accuracy of the logo detection.

The last dataset performance of two logo detection methods on the DeblurGAN-v2 dataset is obtained by applying a preprocessing method called DeblurGAN-v2 to the blurred images. DeblurGAN-v2 is a third method for restoring blurred images, but it uses a generative adversarial network (GAN) to produce realistic and sharp images. It illustrates that YOLOv7 Logo Detection performs better on the DeblurGAN-v2 dataset than on the blur dataset, with mAP scores of 0.748 and 0.71 for the training and testing phases, respectively. Robust Logo Detection performs slightly worse on the DeblurGAN-v2 dataset on the blur dataset, with mAP scores of 0.761 and 0.743 for the training and testing phases, respectively. It then concludes that this indicates that DeblurGAN-v2 is a mixed preprocessing method for improving the performance of the logo detection methods and that it may have different effects depending on the logo detection method used.

4. Conclusion

Based on the process and result, it can concluded that from a combination of image deblurring as preprocessing and logo detection, the best combination is Restormer as preprocessing and Robust Logo Detection as Logo Detection, with PSNR, SSIM, and mAP test of 29.03, 0.8706 and 0.754 respectively. Furthermore, this research shows that Restormer is more robust to blurred images and robust logo detection can detect more accurately for every image using the Flickr-27 dataset. There are many things noise in images one of them is deblurring, so the future works of this research are the other combinations of preprocessing and the logo detection. it will make the logo detection more robust in any condition.

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