

# Super Resolution of Car Plate Images Using Generative Adversarial Networks

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**Abstract**—Car plate recognition is used in traffic monitoring and control systems such as intelligent parking lot management, finding stolen vehicles, and automated highway toll. In practice, Low-Resolution (LR) images or videos are widely used in surveillance systems. In low resolution surveillance systems, the car plate text is often illegible. Super-Resolution (SR) techniques can be used to improve the car plate quality by processing a series of LR images into a single High-Resolution (HR) image. Recovering the HR image from a single LR is still an ill-conditioned problem for SR. Previous methods always minimize the mean square loss in order to improve the peak signal to noise ratio (PSNR). However, minimizing the mean square loss leads to overly smoothed reconstructed image. In this paper, Generative Adversarial Networks (GANs) based SR is proposed to reconstruct the LR images into HR images. Besides that, perceptual loss is proposed to solve the smoothing issue. The quality of the GAN based SR generated images is compared to existing techniques such as bicubic, nearest and Super-Resolution Convolution Neural Network (SRCNN). The results show that the reconstructed images using GANs based SR achieve better results in term of perceptual quality compared to previous methods.

**Index Terms**—Super resolution, car plate, generative adversarial networks

## I. INTRODUCTION

The population and economy of Malaysia have grown significantly from year to year. As a result, the number of vehicles registered in Malaysia have shown significant growth as well. In 2017, the Malaysia Automotive Association (MAA) reported that the total number of vehicle registered in Malaysia reached 28.2 million [1]. The complexity of traffic management becomes a challenge from year to year. Many research had been carried on improving the efficiency and accuracy of vehicle car plate recognition. The car plate recognition algorithms are widely used in traffic monitoring and control systems such as intelligent parking lot management, finding stolen vehicles, traffic law enforcement, automated toll management system for highways, bridges, tunnels and other fields.

In general, car plate recognition consists of four sub-stages, which are car plate localization, car plate extraction, character segmentation and character recognition [2]. In practice, car plate is not the only object in an image that is captured by the camera. Road, cars, people and etc. will also be included in the image as well. Car plate localization stage is designed to analyze the input image and locate the region of interest,

which is the car plate. Next is the car plate extraction stage. This stage is focused on processing the region of interest to extract the car plate. After extraction stage, the acquired extracted area will be the input to the segmentation stage. In the segmentation stage, the image from the extraction stage will be split into several unique parts, where each part contains only one character. Lastly, in the recognition stage, a classifier will be used to recognize the characters from the segmentation stage. Some common classifiers used are Naive Bayes algorithm [3], [4], support vector machine [5] and neural networks [6]. The performance of a car plate recognition system relies on the accurateness of the car plate recognition algorithm and the quality of the image acquisition. However, in practice, Low-Resolution (LR) images or videos are widely used in surveillance systems. In low resolution surveillance systems, the car plate text is often illegible due to the distance, illumination and perspective distortion.

Super-Resolution (SR) techniques can be used to improve car plate image quality by processing a single LR image or a series of LR images into a single High-Resolution (HR) image. Besides that, SR gives an alternative way to solve the limitation of image acquisition from hardware by using software processing. There are two types of SR techniques, which are Single-Image Super-Resolution (SISR) and Multi-Image Super-Resolution (MISR) techniques. SISR techniques can be further categorized into interpolation-based methods [7], reconstruction-based methods [8] and example learning-based methods [9]. For MISR, it can be further categorized into frequency domain method and spatial domain method [10].

## II. PREVIOUS WORKS

Interpolation based method has its advantages and disadvantages depending on the number of pixels need to do the processing [11]. Many researchers had come out with enhanced interpolation based algorithms. Dai et al. [12] proposed an interpolation method by using the images as prior and obtain a better performance. Sarmadi et al. [13] proposed a new approach in SISR. Their method consists of three phases. First phase is the up-sampling phase where interpolation method is implemented. Second stage is the de-blurring stage, a unified probabilistic model is used to remove the blur. The last stage is the de-noising stage where spatially adaptive iterative method

is used to remove noise. As a result, good image is generated in terms of PSNR. However, the maximum magnification factor is limited to only  $2\times$ . Duanmu et al. [14] proposed a new interpolation based algorithm. The edge pixels are detected by Sobel operator. The homogenous areas are filtered in order to find HR image edge pixel value and LR image edge pixel value. The magnification factor is up to  $4\times$ , and the generated images are blurred.

Reconstruction-based methods do not need the training set, instead, HR image needs to be constrained properly in order to increase the quality of super-resolved images. The prior information needed in order to overcome the SISR ill-conditioned problem can be found in the explicit form of distribution or energy functional defined on the class. Zhang et al. [15] proposed a reconstruction based method by integrating K-Singular Value Decomposition (KSV-D) and semi coupled dictionary learning. As KSV-D algorithm training time is less, while the semi coupled dictionary learning is space representation, fusion of this two method result in huge improvement in training time of around  $4\times$ . The quality of the generated images improve as well. Some algorithms are edge-focused methods, which means that they use the interpolation method to reconstruct the image details from a LR input image while concentrating on sharpening the edges. Dai et al. [12], proposed to extract the edges of the input image for the purpose of enforcing their continuity, after that, the output will be blended with the interpolation result to form the super-resolved image. Fattal [16] proposed a method to use the edge statistics to reconstruct the missing high frequency component. However, such method may not able to hold for texture details, the reconstructed images are blurred. Another method of reconstruction-based method is the regularization method. The work in [17] proposed a ‘‘compressive image super-resolution’’ framework to enforce the constraint so that the HR image be sparse in the wavelet domain. Dong et al. [18], [19] proposed a mix mode method. They used the dictionaries of patches and the HR image is calculated by determining an optimization issue with some regularization terms. Shan et al. [20] proposed a fast image upsampling method with a feedback-control scheme performing image deconvolution. In result, computation time reduced dramastically. However, the proposed method does not support large upscaling factor, for example at  $4\times$ .

From the great performance achieved by deep convolutional neural network at ImageNet challenge, various CNN based methods were proposed for super-resolution problem. SRCNN is the first paper that applies CNN to the single image super-resolution problem [21]. SRCNN is a simple model with three convolutional layers working for feature extraction, non-linear mapping, and image reconstruction. This method learns the end-to-end transformation between low and high resolution images. SRCNN used bicubic interpolation to upscale an input image and trained a three layer deep fully convolutional network end-to-end to achieve state-of-the-art SR performance.

### III. METHODOLOGY

This section describes the details of the proposed design implemented in this work. Each architecture of the networks (Generator and Discriminator) are explained in this section. To improve the perceptual quality of the generated image, a perceptual loss function is proposed.

#### A. Proposed Architecture For GANs

GANs consists of two models, Generator Network used to generate a realistic image to fool the Discriminator Network, while the Discriminator Network is used to distinguish the input sample is real or generated. With this method, the Generator is able to learn to build a solution which is very similar to the real image and then the generated image is difficult to be distinguished by the Discriminator. A deep network is proposed in this project. In order to get a stable Deep Convolutional GANs, guideline proposed by Radford et al. [22] is followed when defining the GANs architecture. The suggested guideline are as follows:

- Both Generator Network and Discriminator Network use Batch Normalization layers. The batch normalization layer helps to normalize the input to have zero mean and unit variance to solve the internal co-variate shift.
- Fully connected hidden layers are removed when dealing with deeper network.
- For Generator Network, ReLu activation function is used for all the layers, except for the output layer. The output layer needs to use tanh function as activation. ReLu activation can help the model to learn faster, and cover the color space of the training distribution.
- For Discriminator Network, LeakyReLu activation function is used for all layers. LeakyReLu activation function is found to perform better when deal with higher resolution modeling.

The adversarial mathematics is defined as below:

$$\min_{G_{\theta_G}} \max_{D_{\theta_D}} V(D, G) = E_{I^{HR} \sim p_G(I^{HR})} [\log D_{\theta_D}(I^{HR})] + E_{I^{LR} \sim p_G(I^{LR})} [\log(1 - D_{\theta_D}(G_{\theta_G}(I^{LR})))] \quad (1)$$

where  $p_G(I^{HR})$  is the distribution of HR image,  $I^{HR}$  is the HR image sample for  $p_G(I^{HR})$ ,  $p_G(I^{LR})$  is the distribution of generator based on LR image,  $I^{LR}$  is the LR image sample for  $p_G(I^{LR})$ ,  $G_{\theta_G}(I^{LR})$  is the Generator Network,  $D_{\theta_D}(G_{\theta_G}(I^{LR}))$  is the Discriminator Network.

The equation of ReLu activation function is defined as below:

$$f(x) = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases} \quad (2)$$

LeakyReLu allows a small negative slope of 0.01 in order to fix the ‘‘dying ReLu’’ problem. The equation of LeakyReLu activation function is defined as below:

$$f(x) = \begin{cases} x & x \geq 0 \\ 0.01x & x < 0 \end{cases} \quad (3)$$

1) *Proposed Architecture For Generator Network:* The objective of this project is to train the Generator Network to generate a realistic super resolved car plate images from LR images. In order to achieve that, a feed-forward deep CNN is proposed for the Generator Network which is parametrized by  $\theta_G$ . Where the  $\theta_G$  is  $\{W_{1:L}; B_{1:L}\}$ , which is the weight and bias of the L-layer of the network. The  $\theta_G$  is determined from the loss function.

As the network gets deeper, it is very difficult to train and has a higher training error and validation error. Kaiming et al. [23] proposed a Residual Network (ResNet) to solve the issue. The results show that the training error and validation error is reduced compared to traditional CNN network with the same deep level of the neural network. The concept of the ResNet is pretty simple, it replaces the traditional feed-forward network with skip-connection. Inspired by Kaiming et al. [23], 16 layers of ResNet block with skip-connection is proposed to replace the traditional network. In the proposed Generator Network, a  $3 \times 3$  filter kernel with 64 feature maps and  $1 \times 1$  stride is applied in the input layer and 16 ResNet blocks. In the ResNet block, a batch normalization (BN) layer is used after the convolution layer. A  $3 \times 3$  filter kernel with 256 feature maps and  $1 \times 1$  stride is applied in the upscaling blocks. For the output layer, a  $3 \times 3$  filter kernel with 1 feature map and  $1 \times 1$  stride is applied. All the convolution layers using ReLu activation function, except for output layer, using tanh function to ensure that the output images are in the range of  $[0, 255]$ . Inside the upscaling block, a sub-pixel convolution layer is used to increase the resolution of the input image. Figure 1 shows the proposed Generator Network.

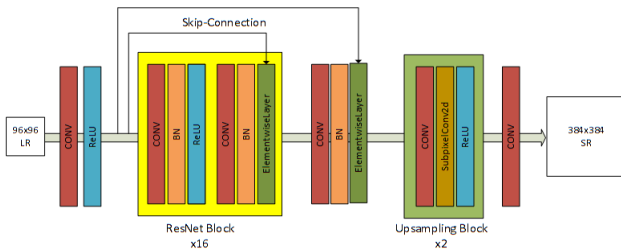


Figure 1. Proposed Generator Network.

2) *Proposed Architecture For Discriminator Network:* The role of the Discriminator Network is to distinguish the real image and the generated image by the Generator Network. In the Discriminator Network, all the convolution layers use LeakyReLu function with  $\alpha = 0.2$  (to prevent maximum pooling throughout the network) as the activation. Inspired by Simonyan et al. [24], the Discriminator Network consists of one input convolution layer and ten hidden convolution layers with  $4 \times 4$  filter kernel. The feature maps is increased for each convolution layer from 64 to 2048 and  $2 \times 2$  stride is applied when the number of feature maps is increased by factor of 2

to reduce the resolution. The h6 and h7 hidden convolution layers apply  $1 \times 1$  filter kernel and  $1 \times 1$  stride with the feature maps reduced by factor of 2 from 2048 to 512. After that, the h8 hidden convolution layer applied  $1 \times 1$  filter kernel and  $1 \times 1$  stride with feature maps of 128. This layer is used as a linear transformation from the previous layer. Next, in h9 hidden convolution layer, a  $3 \times 3$  filter kernel is applied. For the last hidden convolution layer, h10, a  $3 \times 3$  filter kernel with 512 feature maps and  $1 \times 1$  stride is applied. The resulting 512 feature maps are then flattened by using a dense layer and the probability of the sample classification is determined by using sigmoid activation function. A probability range of 0 to 1 indicates how real is the input image that is it, if it tend to be 0, it means the discriminator classifies the input image as a generated image, then the Generator Network will update the parameter  $\theta_G$ , otherwise if the probability is closer to 1, it means the discriminator classifies the input image as a real image, then the Discriminator Network will update its parameter. Figure 2 shows the proposed Discriminator Network.

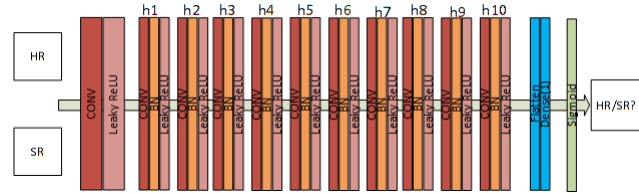


Figure 2. Proposed Discriminator Network.

## B. Loss Function

The loss function plays an important role for the Generator Network's performance. The loss function is the weight sum of the content loss and the adversarial loss, it is defined as:

$$l^{SR} = l_X^{SR} + 0.001l_{Generator}^{SR} \quad (4)$$

where the content loss ( $l_X^{SR}$ ) can be further interpreted as MSE loss and perceptual loss. While the adversarial loss ( $l_{Generator}^{SR}$ ) is determined from the Discriminator Network output. 0.001 is multiplied with the adversarial loss in order to obtain a better gradient behavior.

1) *Adversarial Loss Function:* Adversarial loss has a better performance in restoring the high frequency information (sharp edge) of the constructed image. It is determined from the probability of the Discriminator Network, it is defined as:

$$l_{Generator}^{SR} = \sum_{n=1}^N D_{\theta_D}(G_{\theta_G}(l^{LR})) \quad (5)$$

where  $N$  is number of epochs,  $G_{\theta_G}(l^{LR})$  is the parameter of the generated image from low resolution input image, and  $D_{\theta_D}(G_{\theta_G}(l^{LR}))$  contains the probability of the generated image from Generator Network is a real image. During training, Discriminator Network tries to minimize the probability of the function above while the Generator Network tries to maximize it.

2) *MSE Loss* : The most common loss implemented in SR is the pixel-wise MSE loss. It is defined as:

$$l_{MSE}^{SR} = \frac{1}{r^2WH} \sum_{x=1}^{rW} \sum_{y=1}^{rH} (I_{x,y}^{HR} - G_{\theta_G}(I^{LR})_{x,y})^2 \quad (6)$$

where  $r$  is the scaling factor,  $W$  is the width of the image,  $H$  is the height of the image,  $I_{x,y}^{HR}$  is the ground truth image,  $G_{\theta_G}(I^{LR})_{x,y}$  is the generated image from Generator Network. This pixel-wise MSE loss has a better performance in restoring the low frequency information of the constructed image.

3) *Perceptual Loss*: Since optimizing the pixel-wise MSE loss always results in unsatisfying performance in terms of perceptual perspective, a perceptual loss inspired by Johnson et al. [25] is proposed. This loss function is defined based on a pre-trained 19 layer VGG network. From the VGG19 pre-trained model, the high-level feature maps are extracted by  $j$ -th convolution layer which is after activation layer but before the  $i$ -th maxpooling layer. After extracting the high-level features from VGG19 network, the perceptual loss is defined as the Euclidean distance between the reconstructed image by using these high-level features and the HR image. The perceptual loss function is defined as below:

$$l_{VGG(i,j)}^{SR} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} (\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y})^2 \quad (7)$$

where  $W_{i,j}$  is the weight of the image and  $H_{i,j}$  is the height of the image. These dimensions are extracted from the high-level feature maps of the VGG19 pre-trained model.

$i$  and  $j$  are the number of the convolution layers,  $\phi_{i,j}(I^{HR})_{x,y}$  is the ground truth image and  $\phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y}$  is the generated image by using pre-trained model high level feature maps parameter.

#### IV. RESULTS

In this section, the training details such as the training dataset and the initial hyper parameters will be explained. Next, a comparison between the proposed models using MSE loss as content loss and using MSE + perceptual loss as content loss will be carried out. After that, the proposed model is compared with the existing methods such as bicubic interpolation, nearest neighborhood and SRCNN. All the results are compared with the standard measure metrics such as PSNR and SSIM, and perceptual quality. For fair comparison, the reconstructed images are transformed to gray scale before calculating the PSNR and SSIM. A discussion is carried out to explain why the proposed model has lower PSNR and SSIM results compared to existing methods.

#### A. Training Details

For training dataset and evaluation dataset, dataset adopted from [26] is used. From the dataset, 640 images are randomly chosen as training dataset and another 10 images are chosen as evaluation dataset. For training dataset, the 640 images are pre-processed to  $384 \times 384$  resolution images as the ground truth images, after that the images are downsampled using bicubic kernel by a factor of 4 to obtain  $96 \times 96$  resolution images as low resolution images before being fed into the network. The low resolution images are scaled with a range of  $[0, 1]$  image size while the ground truth images are scaled with an range of  $[-1, 1]$  image size. The MSE loss is calculated on the reconstructed images with an intensity range of  $[-1, 1]$ . The perceptual loss which is extracted from the pre-trained VGG19 model is rescaled by a ratio of  $2E-6$  which is comparable with the MSE loss. In this project, the optimization used is the Adam optimizer [27] with parameter of  $\beta = 0.9$ . The network is trained with 1,000 epochs, with the training rate of  $10^{-4}$  and decay every 500 epoch by 0.1. The batch size of the network is 16. During evaluation, the batch normalization layer is turned off so that the reconstructed images mainly depend on the input images. All the networks are implemented using TensorFlow.

#### B. Validation and Result Collection

For the comparison with the current state-of-art, SRCNN [21] is chosen since it achieved the state-of-the-art performance in terms of PSNR. For fair comparison, the SRCNN [21] model is re-trained from scratch by using our own training images. Since the motivation of this work is to reconstruct the LR car plate image into HR image by using SR method, therefore, 640 HR images which consist of different whole car images are used as the training dataset. The model is trained for 1,000 epochs. In this experiment, all the hyper-parameters are based on Dong et al. [21], a three layer network with  $f_1 = 9$ ,  $f_2 = 5$ ,  $f_3 = 5$ ,  $n_1 = 64$ ,  $n_2 = 32$  with a magnification factor of 4 are used to train the model. Before feeding the input into the model, a pre-processing is done on the input image by using bicubic method to upscale it with a magnification factor of 4.

For validation, 10 images are used in the evaluation set and tested at a upscaling factor of 4. All the images are measured by two different methods: a) standard image quality metrics such as PSNR and SSIM and. b) perceptual quality. For fair comparison, all the images are converted into gray-scale before the measurement of PSNR and SSIM.

#### C. Content Loss Comparison

In this work, two models with different content loss are proposed and analyzed. The first model, which is model A, is trained by using MSE loss only as the content loss. The second model, which is model B, is trained by using MSE loss and the perceptual loss as the content loss. Both models are trained with the same parameters and architecture. The quantitative performance comparison of the content loss

results are summarized as shown in Table I. The visualization performance comparison results are shown in Figure 3

Table I  
QUANTITATIVE COMPARISON OF CONTENT LOSS.

Model	Average PSNR	Average SSIM
MSE	24.8686	0.7213
MSE + Perceptual	23.5185	0.6770



Figure 3. Visual comparison.

From Table I, it clearly shows that the proposed model A with optimized MSE loss only achieves better performance in terms of quantitative metrics compared to the model B with optimized MSE loss and perceptual loss. However, in terms of perceptual result, model A results in a rather blurred appearance and less convincing perceptual performance compared to the model B. This is due to the competition of the MSE-based content loss and the adversarial loss.

#### D. Comparison With Existing Techniques

In here, the model B which is using MSE loss and perceptual loss as the content loss is chosen as the final proposed model. The proposed model is compared with the existing method to analyze the performance of the proposed model. The quantitative performance comparison with existing methods are summarized as shown in Table II. The visualization performance comparison with existing methods are shown in Figure 4 and Figure 5.

Table II  
QUANTITATIVE COMPARISON WITH EXISTING METHODS.

Algorithm	PSNR	SSIM
Nearest Neighborhood	22.1766	0.6397
Bicubic Interpolation	23.5185	0.6770
<b>SRCNN (Dong et al. 2016)</b>	<b>25.4768</b>	<b>0.7067</b>
Proposed	23.0307	0.6760

From Table II, SRCNN achieved excellent performance in quantitative results in terms of PSNR and SSIM. Besides that, in terms of perceptual quality, the proposed method yielded excellent results. As shown in the Figure 4, SRCNN has shown a better perceptual result compared to the bicubic



Figure 4. Visual Comparison With Existing Methods.

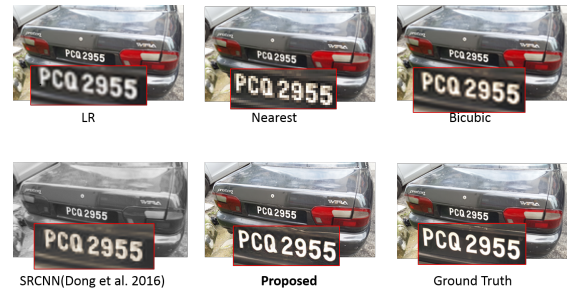


Figure 5. Visual Comparison With Existing Methods.

method. However, since the SRCNN is an end to end mapping method, its performance highly depends on the input image and training images. For example, due to the loss of high frequency information during bicubic interpolation, the over smoothing effect happens at the character “M” which causes the SRCNN image unable to reconstruct the detail information of the character “M”. For the proposed method, it clearly shows that the finer texture details such as character “M” is able to be reconstructed properly and more sensitive to our human perceptual system.

Traditional methods are mainly focused on optimizing the MSE loss only in order to achieve better performance in terms of PSNR and SSIM. By minimizing MSE will tend to maximize PSNR. Clearly, the images obtained by minimizing MSE are overly smoothed (MSE tends to produce an image resembling the mean of all possible high resolution pictures, resulting in a low resolution picture). MSE also does not capture the perceptual differences between the model’s output and the ground truth image. Consider a pair of images, where the second one is a copy of the first, but shifted a few pixels to the left. For a human the copy looks almost indistinguishable from the original, but even such a small change can cause PSNR to decrease dramatically. In addition, several research [28], [29], [25] have proven that high PSNR or SSIM not necessarily yield a better perceptual image. This is due to such metrics always rely on the low-level differences between pixel space. Besides that, MSE highly depends on the image intensity changes. If the generated image has huge difference in intensity with the ground truth image, the value of MSE will increase dramatically.

## V. CONCLUSION

Among the existing SISR methods, SRCNN achieved the best in terms of PSNR and SSIM. Current SISR techniques are not able to reconstruct the information at large upscaling factor whereby the reconstructed image is overly smoothed at the characters. The proposed design has clearly proved that the reconstructed super resolved images are highly aligned with our human perceptual system at large upscaling factor. It is also found that current quantitative metrics that are used to evaluate super resolution images are poorly correlated with our human assessment of visual quality. Traditional methods such as SRCNN and bicubic interpolation are targeted in minimizing the MSE between the reconstructed images and ground truth images, which tends to maximize the PSNR. However, by optimizing the MSE loss, it is proven that the reconstructed images are overly smoothed in appearance. Some high frequency details are not reconstructed properly.

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