Using Generative Adversarial Network techniques to upscale images for Automatic License Plate Recognition

Aleph Campos da Silveira
Federal University of Espírito Santo
Vitória, Brazil
Department of Informatics
Email: aleph.campos@gmail.com

Alessandro M. Baldi
Federal University of Espírito Santo
Vitória, Brazil
Department of Informatics
Email: alessandromurtabaldi@gmail.com

***Abstract*—Transport infrastructure is growing rapidly and changes every day, raising concerns about security systems, with vehicle theft being one of the main problems. With advances in the Artificial Neural Network (ANN) and Deep Learning (DL), better results in vehicle safety can be archived when these techniques are adopted to improve vehicle monitoring like Automated License Plate Recognition (ALPR). This work presents the application of several generative adversarial network (GAN) techniques with the objective of improving the quality of the video image captured by cameras of an autonomous vehicle called Intelligent Autonomous Robotic Automobile (IARA). The purpose of this article is to answer whether GAN techniques can be used to improve the image quality of license plates to retrieve finer details so that an automatic license plate recognition (ALPR) is able to read characters more accurately than the original image. The results were mixed, as training the network was difficult and did not bring satisfactory improvements for very low resolution images. However, some results were surprising as some unexpected license plates could be recovered successfully.**

I. Introduction

Automatic license plate recognition (ALPR) systems are designed to automatically locate vehicle license plates and extract the information contained in the image such as characters from a vehicle registration plate using optical character recognition (OCR) technique. ALPRs applications are important for automatic toll collection, traffic law enforcement, parking access control, road traffic monitoring and vehicle security, as they can be used to identify vehicle theft [1] [2].

However, the recognition performance of an ALPR system is affected by conditions such as variable lighting, viewing angle, different plate sizes, contrast and shadows. In addition, the resolution of the plate, the size of the characters make the work of OCRs difficult, which degrades the accuracy of recognition. Low resolution images, usually when the vehicle is too far from the camera, can make it difficult to use for practical purposes. To solve this problem, this work proposes the adoption of Deep Learning (DL) techniques to improve the quality of the images so that an OCR is able to better recognize the characters of low resolution license plates. [2]

With recent developments in artificial neural networks (ANN), deep learning (DL), novel algorithms and techniques have become attractive to researchers in a plethora of fields. Among those are studies of Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN). The latter (GANs) are types of structures that started to gain attention in the super-resolution literature. These architectures consist of two neural networks working simultaneously to beat each other. SRGAN, one of the first examples of successful super-resolution GANs, has managed to increase the resolution of an image by up to four times the scale factor with high performance (Figure II-B). This upscale is being used to improve a variety of entertainment media quality, such as 3D video game textures or image quality from old movies and cartoons. Why not use it to improve traffic image quality that would facilitate vehicle identification?

An ALPR system extracts the plate number of a given image in four steps [3]

1) The first step is to acquire the image of the car through a camera. Camera parameters, such as camera type, camera resolution, shutter speed, orientation and light, must be considered.
2) The second step is to extract the plate from the image based on some characteristics, such as the limit, the color or the existence of the characters.
3) The third step is to segment the board and extract the characters by projecting their color information, labeling them or combining their positions with models.
4) The final stage is to recognize the characters extracted by combining models or using classifiers, such as neural networks and fuzzy classifiers.

This work focuses between the third and fourth step. After the license plate was cropped from the image, GAN techniques were applied to improve the resolution so that an OCR could read and extract the characters.

This work seek to improve the specifics characters of car license plates by at least 4x upscaling factor that can aid in the identification of a stolen car by the use of a perceptual loss mechanism that consists of an adversarial loss and a content loss [4]. The tools and techniques used in this work will be presented below.

II. Generative Adversarial Networks

A generative adversarial network (GAN) is a class of machine learning frameworks designed by Ian Goodfellow and his colleagues in 2014[5]. Two neural networks contest with each other in a game in the form of a zero-sum game, where one agent's gain is another agent's loss. The generative network generates candidates while the discriminative network evaluates them. Typically, the generative network learns to map from a latent space to a data distribution of interest, while the discriminative network distinguishes candidates produced by the generator from the true data distribution. The generative network's training objective is to increase the error rate of the discriminative network.

A dataset serves as the training data for the discriminator that involves presenting it with original samples until it achieves acceptable accuracy. For the generator, it trains based on whether it succeeds in fooling the discriminator or not. Typically the generator is seeded with randomized input that is sampled from a predefined latent space. Thereafter, candidates synthesized by the generator are evaluated by the discriminator. Independent backpropagation procedures are applied to both networks so that the generator produces better samples, while the discriminator becomes more skilled at flagging synthetic samples. When used for image generation, the generator is typically a deconvolutional neural network, and the discriminator is a convolutional neural network.

GANs are used in a number of applications, like entertainment, art, science and are even raising some concerns about its use in deepfakes[1]. In any case, its application brings surprising results, as shown below.

A. SRGAN

Super-resolution (SR) is a process of estimating a high-resolution (HR) image from its low-resolution (LR) counterpart [6]. SRGAN is a implementation of a GAN for single image upscalling. As others GANs, it uses a perceptual loss function which consists of an adversarial loss and a content loss with two neural networks that exchange values between them. The generative network pushes the solution to the natural image manifold using a discriminator network that is trained to differentiate between the super-resolved images and original photo-realistic images. An example of GAN application for Super Resolution (SRGAN) and their results can be seem in Fig 1 and [4].

A number of variations of this technique currently exist, such as the next shown below.

B. ESRGAN

ESRGAN is a SRGAN variant with improved network architecture, adversarial loss and perceptual loss [7]. To train a neural network easier, ESRGAN adds the Residual-in-Residual Dense Block (RDDB), eliminates Batch Normalization (BN)

[1]Deepfakes are synthetic media in which a person in an existing image or video is replaced with someone else's likeness

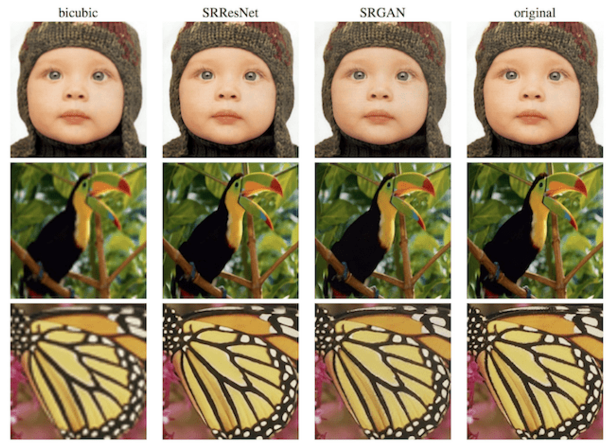


Fig. 1. Example of GAN-Generated Images With Super Resolution. Taken from Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network, 2016.

layers, and uses residual scaling and smaller initialization. To the generator recover more detailed texture information, ESRGAN uses Relativistic average GAN (RaGAN) to improve the discriminator. Another aspect is that the VGG functions are used before activation rather than after activation, which helps in improved perceptual loss.

Fig. 2. Comparative of SRGAN, ESRGAN and Ground Truth. Taken from ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks, 2018.

ESRGAN can produce better, sharper and more natural textures, according to Wang et al [7].

C. DLSS

Deep Learning Super Sampling or DLSS is Nvidia's proprietary hardware-accelerated SR technique which was introduced during the GTC 2018 keynote and uses a datacenters of computers to train the DLSS neural network for each application. Given this, for this work it was used an open-source version of this network generic called *Neural Super Sampling*. Some results can be see in Fig.3

DLSS does not enhance the image, but makes it sharper and smoother, so it was applied when the results of other GAN techniques were pixelated.

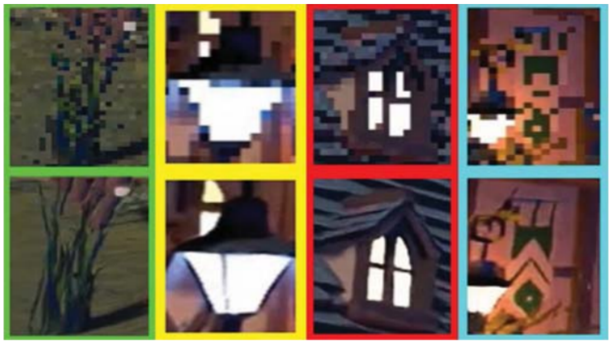


Fig. 3. Comparison between NSS input and output renders at 30x magnification. Source: [6]

D. SRFEAT

SRFeat is a Single Image Super-Resolution with Feature Discrimination that employs two discriminators to generate perceptually pleasant pictures: an image discriminator and a feature discriminator. The generator network may provide perceptually realistic Super Resolution solutions thanks to the feature discriminator. This unique generator, according to the authors, delivers state-of-the-art PSNR performance when compared to similar techniques with the same number of parameters [8].

E. ERCA

ERCA is a GAN-based Single Image Super Resolution with Dual Discriminator and Efficient Residual Channel that employs a new generator architecture that skip connection, channel attention, batch norm removal, and mean absolute error loss training [9].

F. EDSR

The enhanced deep super-resolution network (EDSR) uses an improved SRResNet architecture to simplify the network design by eliminating unneeded modules. It presents a new multi-scale architecture that uses residual scaling approaches to train models while sharing most of the parameters across scales. The suggested multi-scale model, according to the authors, has fewer parameters than multiple single-scale models but performs similarly to the single-scale Super Resolution model [10].

III. Method

Given these results, the present work seeks to apply GAN techniques to improve the quality of license plate images so that an ALPR system is able to recognize characters with an OCR, since images such as the one in Figure 4 results in errors:

The program produces two outputs:

- The first is a super resolution of a picture that is more detailed. The user should simply use such an image for better alphanumeric visualization.
- An ALPR were applied to the output image, transcribing the license-plate characters.

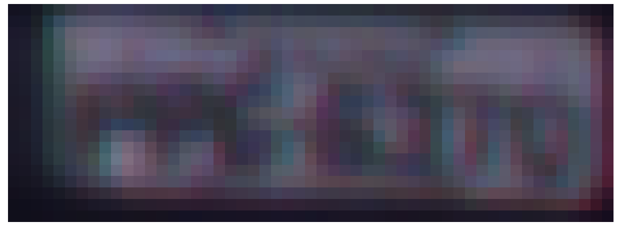


Fig. 4. Example of low resolution images of license plates. Source: IARA Dataset

For this work, the IARA Data Set was used for testing. IARA Data Set is a set of images from the High Performance Computing Laboratory of the Federal University of Espírito Santo that is researching on an automatic vehicle called Intelligent Autonomous Robotic Automobile (IARA). For training, a dataset of license plates from the Federal University of Parana was used (UFPR ALPR) and a Dataset of others works found on Github. SRGAN was used with raw images, SRGAN with cropped plates from images, ESRGAN with cropped plates from images, SRGAN pre-trained with landscapes images, and ESRGAN pre-trained with chinese plates.

The SRGAN and ESRGAN was based on Ledig et al [4] and [11] respectively. The follow algorithm is a simplification of the process:

Algorithm 1 Upscalling License Plate Images with SRGAN

BEGIN
Pre-processing of the the IMAGE DATA SET from RGB to GRAYSCALE
Train **SRGAN** OR **ESRGAN** with raw or cropped UFPR ALPR data set containing **HIGH / LOW RESOLUTION IMAGES** of License Plates
Load **LOW RESOLUTION IMAGE** from IARA Dataset as a test image
if HIGH PIXELATION **then**
    Run DLSS for antialiasing
Run a ALPR system in order to correctly identify the license plate
END

IV. Dataset Setup

The datasets used in the experiment are real-world photos in which both the vehicle and the camera are inside a moving vehicle. These images are pre-processed and used for training, testing and validation of the deep learning algorithms for upscaling plates.

A. UFPR ALPR Dataset

UFPR ALPR is a dataset from Federal University of Paraná that was released for academic study and is available for non-commercial use. It consists of 3500 PNG (Portable Network Graphics) images of 150 vehicles captured by GoPro Hero4 Silver, Huawei P9 Lite, and iPhone 7 Plus cameras with a resolution of 1,920 x 1,080 pixels. The dataset is public and open for use in accordance with the terms and conditions of the agreement.

An OpenCV based algorithm was used to pre-process the dataset for automatic cropping of the license plate. After this, low resolution images were manually discarded so the SRGAN and ESRGAN algorithms could be properly trained.

B. IARA Dataset

IARA (Intelligent Autonomous Robotic Automobile) is a dataset created by the Federal University of Espirito Santo's (UFES) High-Performance Computing Lab (LCAD), which developed the IARA autonomous vehicle. Iara dataset includes images of other cars taken by camera sensors during IARA self-driving car experiences on city streets. The dataset for our experiment was provided by LCAD and because of the high volume of traffic, the *Dante Michelini Avenue* was chosen. The dataset is in a proprietary format that requires the converter utility tool to convert into an image [2].

The image was cropped using the Labelbox platform. Labelbox is a crowdsourcing tool that helps in creating high-quality datasets by the use of human annotations. To annotate the plates in images, a task of plate segmentation was created in Labelbox and distributed to LPRM (Multimedia and Networking Research Lab) workforce.

After completing the tasks in Labelbox, a post-processing algorithm was applied to cut the plates of the IARA image dataset. These plates obtained by the database algorithm were used to test and validate the Deep Learning algorithms.

C. Dataset of Other Works (Github)

Dataset of other works found on Github is a compilation of images of Brazilian vehicles and license plates, containing a wide range of images with different resolutions and formats.

Images in the dataset were manually pre-processed, excluding those that were blurry, crooked or with inadequate lighting or resolution. The images were placed on the Labelbox platform and annotated by LPRM[3] workforce. After completing the Labelbox tasks, an algorithm took the data and cut the images. This images were also used in training and testing the ESRGAN and SRGAN algorithms.

V. Training

The training was carried out with the two sets of data mentioned. Initially, training with RAW UFPR ALPR images demonstrated a very large training time and a lack of convergence of the algorithm still in the pre-training of the generator. Thus, images of the Region of Interest (cropped images) were used in the training, accelerating and improving the results of the algorithm. The cropped data sets were adapted to the resolution of each of the standard configuration of the SRGAN (96x96), ESRGAN (192x96) and DLSS (128x128).

The following table presents the algorithms and datasets used for attempts in training:

Number	Algorithm	Dataset of Training
1	SRGAN	Cropped UFPR ALPR
2	ESRGAN	Cropped UFPR ALPR
3	SRGAN	Cropped Dataset of Other Works
4	ESRGAN	Cropped Dataset of Other Works

TABLE I
ALGORITHMS

Training with the UFPR ALPR showed that low-resolution images of the dataset made it difficult for the algorithms to function properly due to poor image quality, like inadequate position of the camera, unfavorable lighting and shadows. Thus, the algorithms converged very quickly and the SnRatio and PSNR test values did not represent the same training values. The dataset was then discarded in this work, remaining the approaches 3 and 4.

VI. Limitations

A. SRGAN

- Time cost to train: The algorithm took more time to train compared to others GAN techniques.
- GPU cost: Depending on the size of the dataset, the algorithm may not complete because the overflow of Google Collab RAM and VRAM.

B. ESRGAN

- Input resolution: the algorithm only accepts 192 x 96 resolution images.
- Training more than 9 epochs results in RAM overflow.

C. DLSS

The DLSS improves the image by methods of supersampling, removing aliasing (jagged and pixelated edges) and not by upscalling it. So this method was only used to improve high pixelated images resulted from the previously algorithms.

VII. Results

The comparison results, the IARA dataset worked under different algorithms with pre-trained image weights from the dataset DIV2K[4]: SRGAN, SRFEAT, ESRGAN, ERCA and EDSR. The algorithms and pre-treined weights are in github project [5].

The following are the ground-truth and the generated images. For better visualization of the ground-truth/original images and those generated by the algorithms, see link[6] :

[2]https://github.com/LCAD-UFES/carmen_lcad/tree/master/src/utilities/convert_log_images

[3]Laboratório de Pesquisa em Redes e Multimídia

[4]https://data.vision.ee.ethz.ch/cvl/DIV2K/)

[5]https://github.com/hieubkset/Keras-Image-Super-Resolution

[6]https://github.com/PhelaPoscam/DeepLearning-2021-01/tree/main/Comparative

Fig. 5. IARA DATASET

Fig. 6. SRGAN

Fig. 7. SRFEAT

Fig. 8. ESRGAN

Fig. 9. EDSR

Fig. 10. ERCA

Next graph shows the identified images by the ALPR. The higher the score, the closer of the characters on the board.

The generated output has a higher ALPR score than the ground-truth image, improving license plate recognition. It should be noted that with pre-trained values there is a possibility to improve image quality using SRGAN and ESRGAN compared to training values obtained in training with our personal dataset, due to our being limited to only 96 images. Bigger datasets should improve our results considerably.

Generative Adversarial Networks are difficult to train and it is not recommended to let them "train alone" as they do not converge. Instead, the generator and the discriminator models find a stable equilibrium. The generator deceives the discriminator at some level and the discriminator effectively classifies real and generated images. A standard procedure is that you must save models frequently during training, then post-hoc evaluate them by the images they generate in order

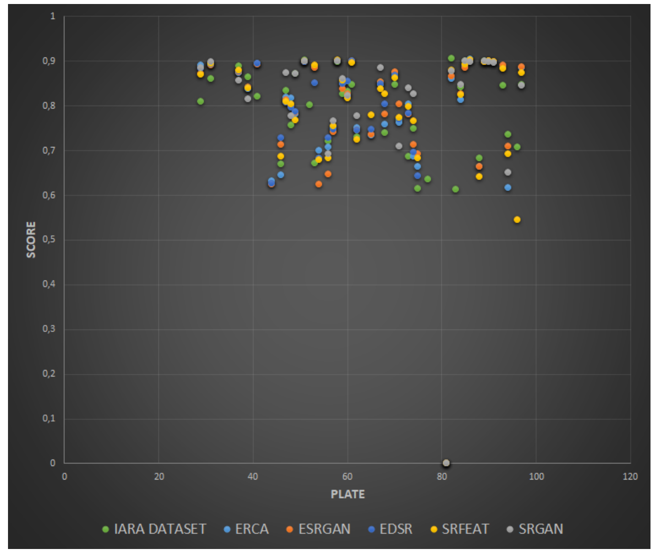


Fig. 11. Comparison of Algorithms

to choose a final model[12]. The best results were achieved when the best generated images were manually chosen.

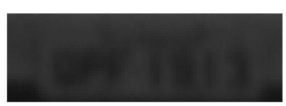
Finally, the results of the algorithms were compared with an OCR code, using the original image and the output generated by the algorithms. The accuracy level of the characters in each output has been registered as below:

Original 96x33
Source: IARA Dataset

Result 384x144
Source: Authors

Original 96x33
Source: IARA Dataset

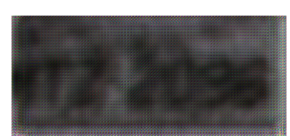
Result 384x112
Source: Authors



Original 96x33
Source: IARA Dataset

Result 384x144
Source: Authors

Original 96x33
Source: IARA Dataset



Result 384x144
Source: Authors

Original 96x33
Source: IARA Dataset

Result 384x144
Source: Authors

The following table presents the results of the ALPR with ground-truth low resolution images with the generated high resolution output of the SRGAN. " Recognized plate " is the plate recognized by the algorithm and " Score " is the accuracy of the plates recognized by the ALPR algorithm. "Candidates" present themselves as possible solutions to the license plate.

File	Recognized Plate	Score	Candidates
IARA_LR_1.png	mqi7577	0,687	[{’score’: 0.687, ’plate’: ’mqi7577’}, {’score’: 0.686, ’plate’: ’hqi7577’}]
IARA_HR_1.png	mqi7577	0,752	[{’score’: 0.752, ’plate’: ’mqi7577’}, {’score’: 0.732, ’plate’: ’mqi7977’}, {’score’: 0.674, ’plate’: ’hqi7577’}, {’score’: 0.656, ’plate’: ’mqi7571’}, {’score’: 0.654, ’plate’: ’hqi7977’}, {’score’: 0.644, ’plate’: ’mqi9577’}, {’score’: 0.636, ’plate’: ’mqi7971’}, {’score’: 0.624, ’plate’: ’mqi9977’}, {’score’: 0.579, ’plate’: ’hqi7571’}, {’score’: 0.566, ’plate’: ’hqi9577’}]
IARA_LR_2.png	mps1036	0,835	[{’score’: 0.835, ’plate’: ’mps1036’}, {’score’: 0.833, ’plate’: ’mps1o36’}, {’score’: 0.777, ’plate’: ’mps1035’}, {’score’: 0.776, ’plate’: ’mps1o35’}]
IARA_HR_2.png	mps1036	0,849	[{’score’: 0.849, ’plate’: ’mps1036’}, {’score’: 0.848, ’plate’: ’mps1o36’}, {’score’: 0.81, ’plate’: ’mps1035’}, {’score’: 0.809, ’plate’: ’mps1o35’}]
IARA_HR_3.png	-	-	-
IARA_LR_3.png	bpf1813	0,616	[{’score’: 0.616, ’plate’: ’bpf1813’}, {’score’: 0.608, ’plate’: ’gpf1813’}, {’score’: 0.607, ’plate’: ’bpp1813’}, {’score’: 0.604, ’plate’: ’bpf1913’}, {’score’: 0.599, ’plate’: ’gpp1813’}, {’score’: 0.597, ’plate’: ’gpf1913’}, {’score’: 0.595, ’plate’: ’bpp1913’}, {’score’: 0.588, ’plate’: ’gpp1913’}]
IARA_HR_4.png	-	-	-
IARA_LR_4.png	-	-	-
IARA_LR_5.png	ppr8752	0,635	[{’score’: 0.635, ’plate’: ’ppr8752’}, {’score’: 0.631, ’plate’: ’ppg8752’}, {’score’: 0.625, ’plate’: ’ppr8152’}, {’score’: 0.622, ’plate’: ’ppg8152’}, {’score’: 0.611, ’plate’: ’hpr8752’}, {’score’: 0.607, ’plate’: ’hpg8752’}, {’score’: 0.601, ’plate’: ’hpr8152’}, {’score’: 0.598, ’plate’: ’hpg8152’}, {’score’: 0.54, ’plate’: ’ppr8754’}, {’score’: 0.537, ’plate’: ’ppg8754’}]
IARA_HR_5.png	-	-	-

TABLE II
CORRECTLY RECOGNIZED PLATES

Mixed results can be seen. Although the images were improved based on the number of pixels, some very low resolution images could not be improved and the results are not always satisfactory. One of the reasons is the limited dataset that were used in this work.

VIII. CONCLUSION AND CHALLENGES

The model can be used in low-resolution cameras to capture license plates and recognize stolen vehicles. It can also be applied to the recognition of traffic plates and road markers to improve conduction of automated vehicle.

However, using of GANs can be problematic: although the results generated by GANs can be remarkable, it can be challenging to train a model as the training process is inherently unstable because both the generator and the discriminator model are trained simultaneously.

Salimans [13] states that "Training GANs consists of finding a Nash equilibrium for a two-player non-cooperative game [and] finding a Nash equilibrium is a very difficult problem", also stating that "the generative adversary networks lack of an objective function, which makes it difficult to compare the performance of different models." Another problem is that measurement results can be complicated, as cited by the authors of the SRGAN implementation that was used for this work [14]: "we we show that standard quantitative measures like PSNR and SSIM fail to accurately capture and assess image quality relative to the human visual system." The same goes for [13]: "An intuitive performance metric can be obtained by making annotators humans to judge the visual quality of the samples."

The results of this work showed that super-resolution upscaling of extremely low license plate images can be difficult to be done without further post-processing image enhancements.

Some results in particular were unexpected: although the SRGAN returned a better quality image, it was surprising that it did not increase the OCR accuracy.

ESRGAN did not show expected results, as it is intended to be a improvement of the SRGAN. Originally, the ESRGAN code was trained with Chinese plates and uses its own reduction algorithm to insert and retrieve the plate (CSI style). The original values of this network are overfitted for two main points:

1) Downsizing performed by other tools (other than the author's own algorithm) does not retrieve good results.
2) The algorithm is able to retrieve highly pixelated plates that have been trained only from the images used in his own network training and testing.

Fig. 11 shows the ESRGAN test using a image from the dataset. The algorithm tries to show other letters, as demonstrated by the result.

Fig. 12. Example of not recovered pixelized image in ESRGAN.

However, Fig 12 shows that one pixelated image that were already used in the training could be perfectly recovered.

A. Future directions

Our interest in this work is retrieve characters from low resolution license plates and not the development of a novel GAN algorithm, so its plausible to recommend the use of multiple methods to improve the ground-truth image. Also,

Fig. 13. Example of recovered pixelized image in ESRGAN.

for best results, a pre-processing standardization process for low resolution is encouraged as it would improve the generated output of those GAN techiniques, as it would permit the use of a artificial generated dataset that could be used for training, as using Generative Adversarial Networks for creation of a dataset is a direct recommendation for future works by the authors.

A natural implications of our results is that quantitative values such as PSNR and SSIM are not suitable to qualify an image. One of the proposals is an OCR checker that would identify characters in license plates during the training and assist in the GAN training process, mitigating the risks of overfitting.

References

[1] A. Baldi, V. F. Mota, and C. A. Santos, "Crowd-auto: Locating theft vehicles through urban crowdsensing," in *Proceedings of the Brazilian Symposium on Multimedia and the Web*, 2020, pp. 61–64.

[2] K. Khan and M.-R. Choi, "Automatic license plate detection and recognition framework to enhance security applications," *Journal of electronic imaging*, vol. 28, no. 1, p. 013036, 2019.

[3] S. Du, M. Ibrahim, M. Shehata, and W. Badawy, "Automatic license plate recognition (alpr): A state-of-the-art review," *IEEE Transactions on circuits and systems for video technology*, vol. 23, no. 2, pp. 311–325, 2012.

[4] C. Ledig, L. Theis, F. Huszár, J. Caballero, A. Cunningham, A. Acosta, A. Aitken, A. Tejani, J. Totz, Z. Wang *et al.*, "Photo-realistic single image super-resolution using a generative adversarial network," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2017, pp. 4681–4690.

[5] I. J. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial networks," *arXiv preprint arXiv:1406.2661*, 2014.

[6] K. Kapse, "An overview of current deep learned rendering technologies," in *2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS)*, vol. 1, 2021, pp. 1404–1409.

[7] X. Wang, K. Yu, S. Wu, J. Gu, Y. Liu, C. Dong, Y. Qiao, and C. Change Loy, "Esrgan: Enhanced super-resolution generative adversarial networks," in *Proceedings of the European Conference on Computer Vision (ECCV) Workshops*, 2018, pp. 0–0.

[8] S.-J. Park, H. Son, S. Cho, K.-S. Hong, and S. Lee, "Srfeat: Single image super-resolution with feature discrimination," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 439–455.

[9] H. T. Hoang, T. X. Nguyen, and N. V. An, "Image enhancement a erca: Gan-based single image super resolution with dual discriminator and efficient residual channel attention," 2019.

[10] B. Lim, S. Son, H. Kim, S. Nah, and K. Mu Lee, "Enhanced deep residual networks for single image super-resolution," in *Proceedings of the IEEE conference on computer vision and pattern recognition workshops*, 2017, pp. 136–144.

[11] Z. Zhang and C. Cai, "License plate enhancement - from tv shows to reality," https://github.com/zzxvictor/License-super-resolution, 2020.

[12] J. Brownlee, "How to evaluate generative adversarial networks," in *Machine Learning Mastery*, 2019.

[13] T. Salimans, I. J. Goodfellow, W. Zaremba, V. Cheung, A. Radford, and X. Chen, "Improved techniques for training gans," *CoRR*, vol. abs/1606.03498, 2016. [Online]. Available: http://arxiv.org/abs/1606.03498

[14] F. H. J. C. A. C. A. A. A. A. A. T. J. T. Z. W. W. S. Christian Ledig, Lucas Theis, "Photo-realistic single image super-resolution using a generative adversarial network," in *arXiv*, 2016.